

# GIS Community of Practice Monthly Forum

Last Wednesday of the month

Wednesday, February 28<sup>th</sup> , 2024  
1:30 – 2:30 PM



California  
DEPARTMENT OF TECHNOLOGY  
STRATEGY INNOVATION DELIVERY





# GIS Community of Practice (CoP)

- Welcome to the GIS CoP forum.
- For the best experience, please use your computer to join the meeting.
- Mute your audio.
- Turn off your video unless you're presenting or in active discussion.
- Use the raise hand button or the meeting chat for comments and questions.
- We will begin shortly.

# GIS CoP Agenda

## Welcome

- Lothar Petrik, CDT Data Engineering Architect

## Main Topics

- Jim Spero, CalFire ([jim.spero@fire.ca.gov](mailto:jim.spero@fire.ca.gov))  
"Examining Building Footprint Sources"
- Fennis Reed, Department of Finance ([fennis.reed@dof.ca.gov](mailto:fennis.reed@dof.ca.gov))  
"Small Area (population) Estimates"

## Announcements

- Open to members

## Conferences/ Events

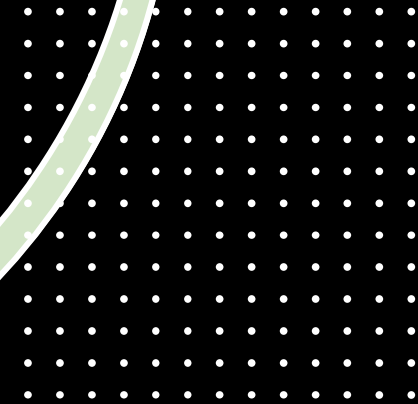
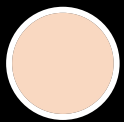
- [CalGIS](#) – March 18-20, 2024 – Visalia, California
- ESRI User Conference – July 15-19, 2024 – San Diego, California

# Strengths of Building Footprint Sources

GIS Community of Practice Meeting

2/28/2024

Jim Spero



# FRAP Use Case – WUI Definition

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FRAP needs to characterize areas to reflect the relative exposure of urban assets at risk from wildfires

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Traditionally we have used US Census block density (housing units) to develop density maps for WUI definition

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Higher spatial resolution is desirable

# Sources

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## Structures USA

10,931,401 buildings

Oak Ridge National Laboratory (ORNL)

Federal Emergency Management Agency (FEMA) Geospatial Response Office

## Microsoft Building Footprints

12,886,951 buildings

The 2018 and 2020 Microsoft non-overlapping building footprints were merged to create a composite dataset and building footprint data was added from counties where available.

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# Comparisons

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## Buildings USA (FEMA / Oak Ridge NL / USGS)

- Commercially available satellite imagery
- Buildings >450 sq feet
- Occupancy type from Census Housing Unit data, HIFLD, LightBox parcels and modeling.
- For Flood Insurance Mitigation, Emergency Preparedness and Response
- Maintained over time

## MS Footprints

- From Bing Maps imagery using deep learning object classification methods
- Building outlines only
- For urban planning and risk assessment



### Structures USA (CA)

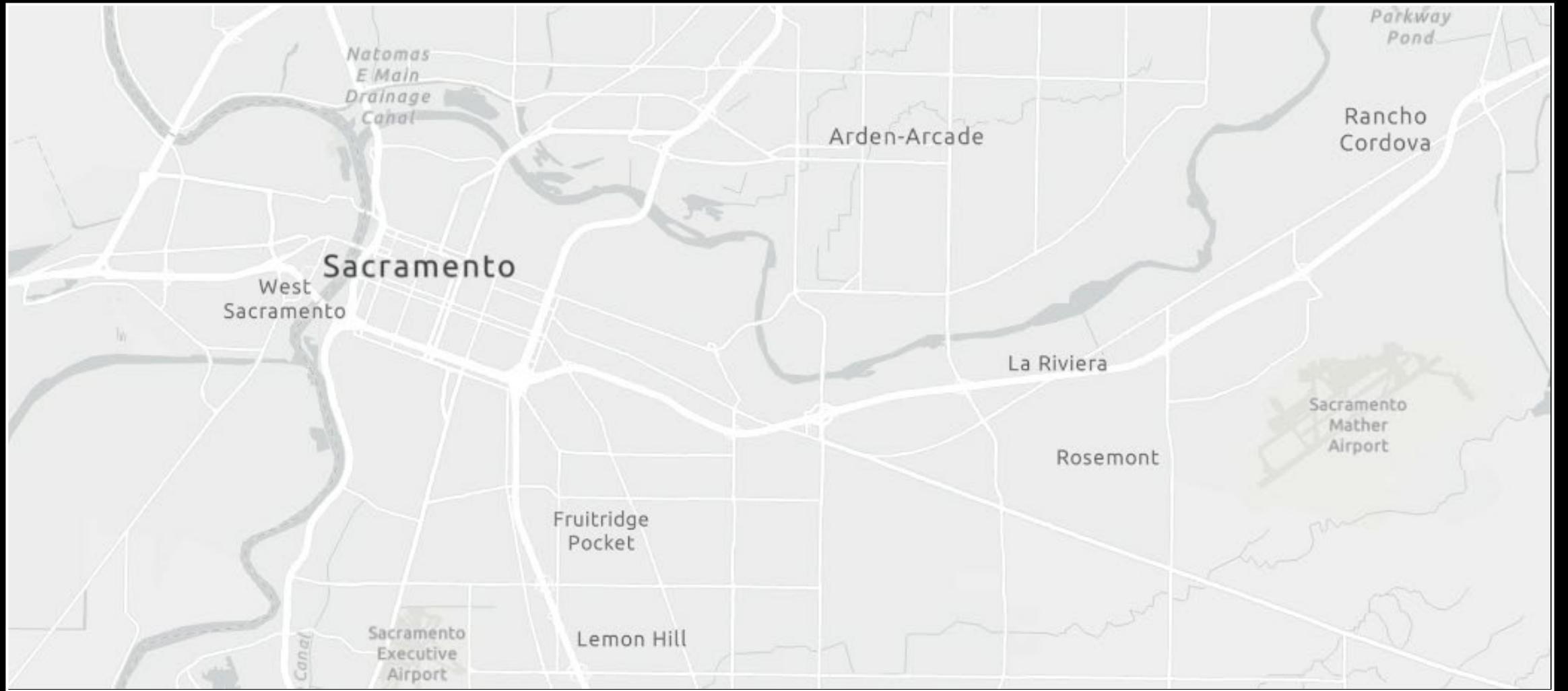
OCC_CLS	Records	Percent
Agriculture	119,372	1%
Assembly	33,494	0%
Commercial	317,529	3%
Education	64,217	1%
Government	73,980	1%
Industrial	142,333	1%
Residential	9,901,603	91%
Unclassified	272,246	2%
Utility and Misc	6,627	0%
	10,931,401	100%

# Occupancy Class

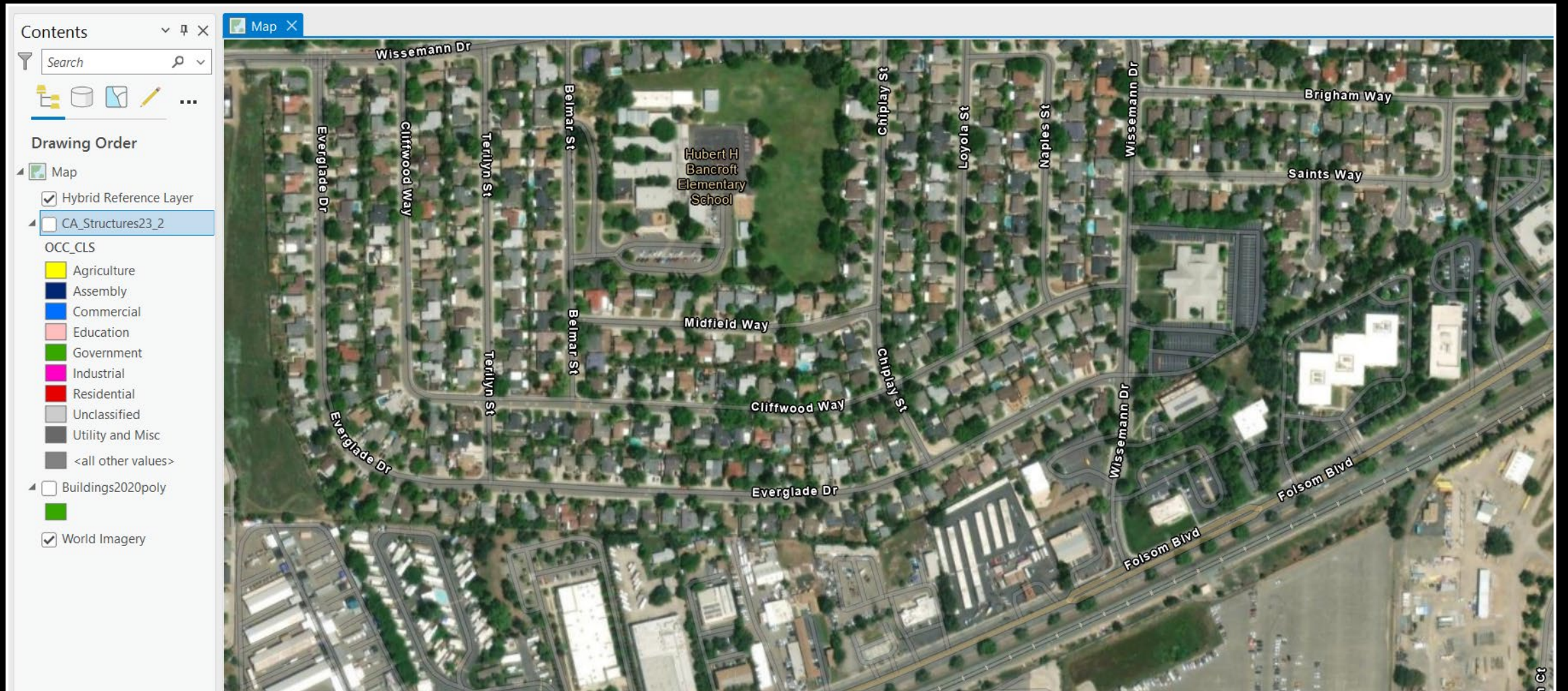
OCC\_CLS



PRIM_OCC	Count
1 Agriculture	119,372
2 Aviation	1,423
3 Banks	17
4 Colleges/Universities	17,838
5 Community Center	8,498
6 Construction	1,109
7 Convention Center	427
8 Emergency Response	4,215
9 Energy Control Monitoring	521
10 Entertainment and Recreation	30,802
11 Food/Drugs/Chemicals	8,004
12 General Services	45,272
13 Ground	3,416
14 Heavy	7,972
15 High Technology	1,343
16 Hospital	2,395
17 Indoor Arena	597
18 Institutional Dormitory	4,911
19 Light	115,563
20 Manufactured Home	418,422
21 Marine	1,242
22 Medical Office/Clinic	8,727
23 Metals/Minerals Processing	8,357
24 Multi - Family Dwelling	1,172,700
25 Non-Civilian Structures	24,507
26 Nursing Home	7,949
27 Other Educational Buildings	9,728
28 Parking	3,697
29 Personal and Repair Services	37,378
30 Pre-K - 12 Schools	36,559
31 Professional/Technical Services	69,581
32 Rail	95
33 Religious	23,830
34 Retail Trade	151,873
35 Single Family Dwelling	8,275,106
36 Stadium	124
37 Temporary Lodging	22,569
38 Theaters	414
39 Unclassified	272,246
40 Veterinary/Pet	754
41 Wholesale Trade	11,848
ALL	10,931,401

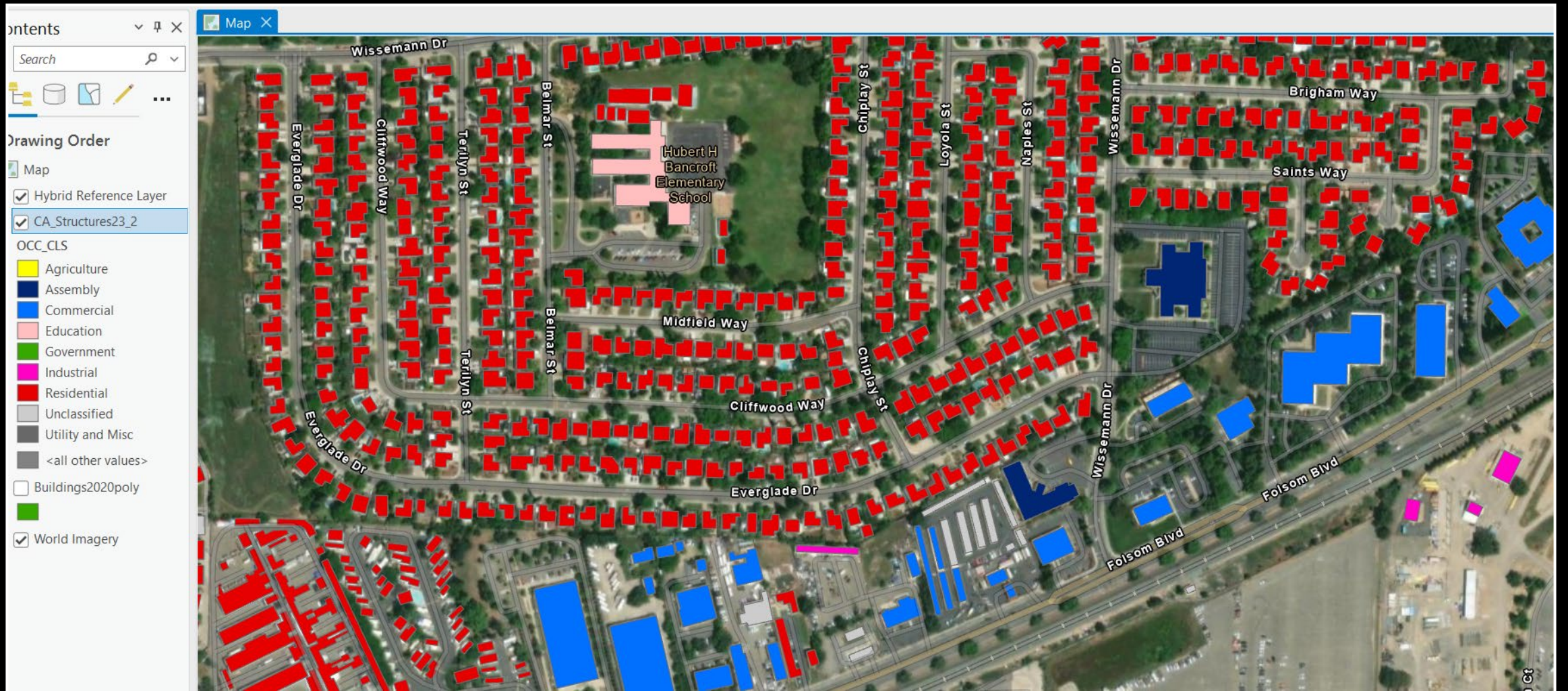


Zooming into an urban area....



Structures USA (CA) – Urban Area

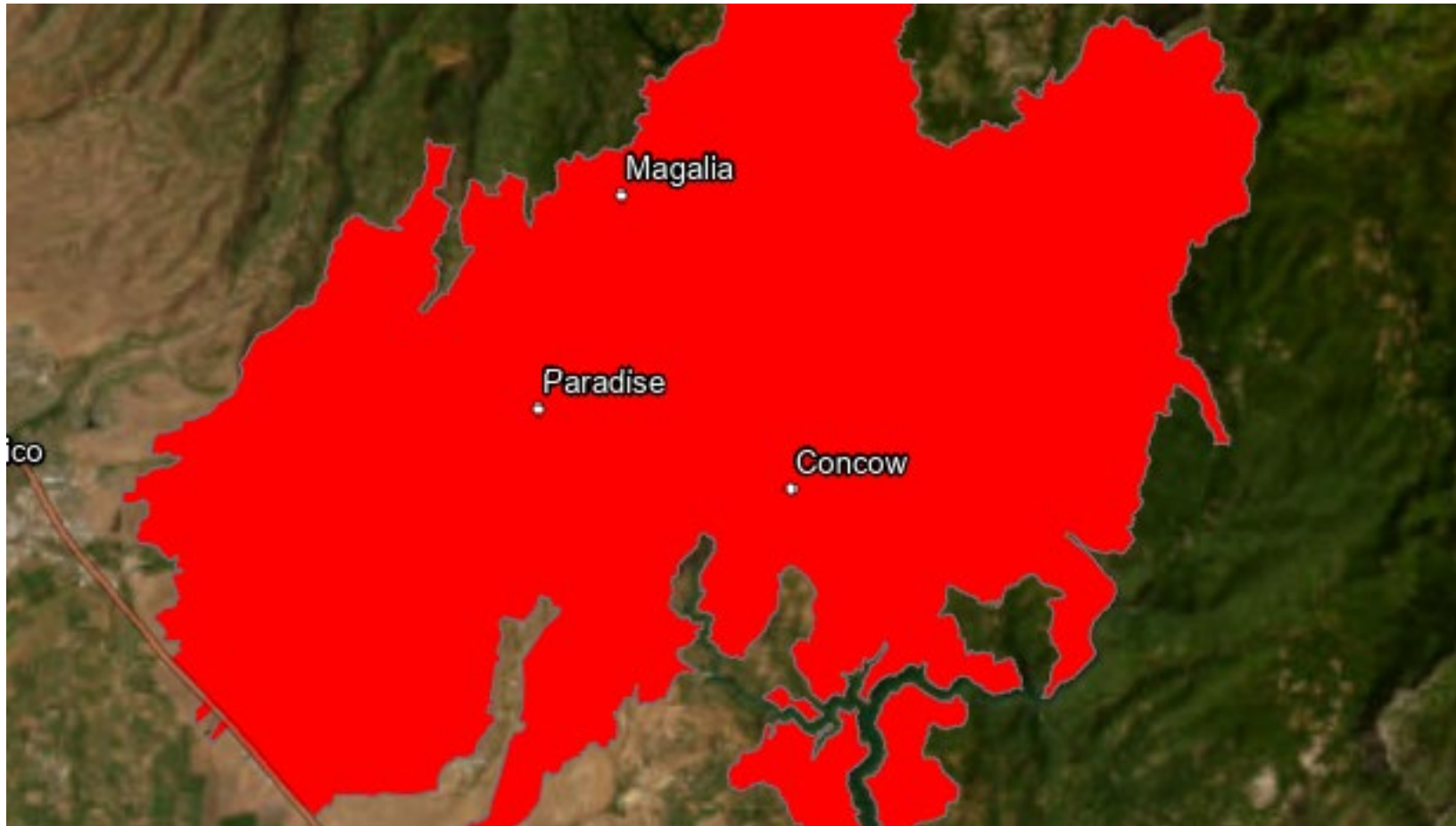




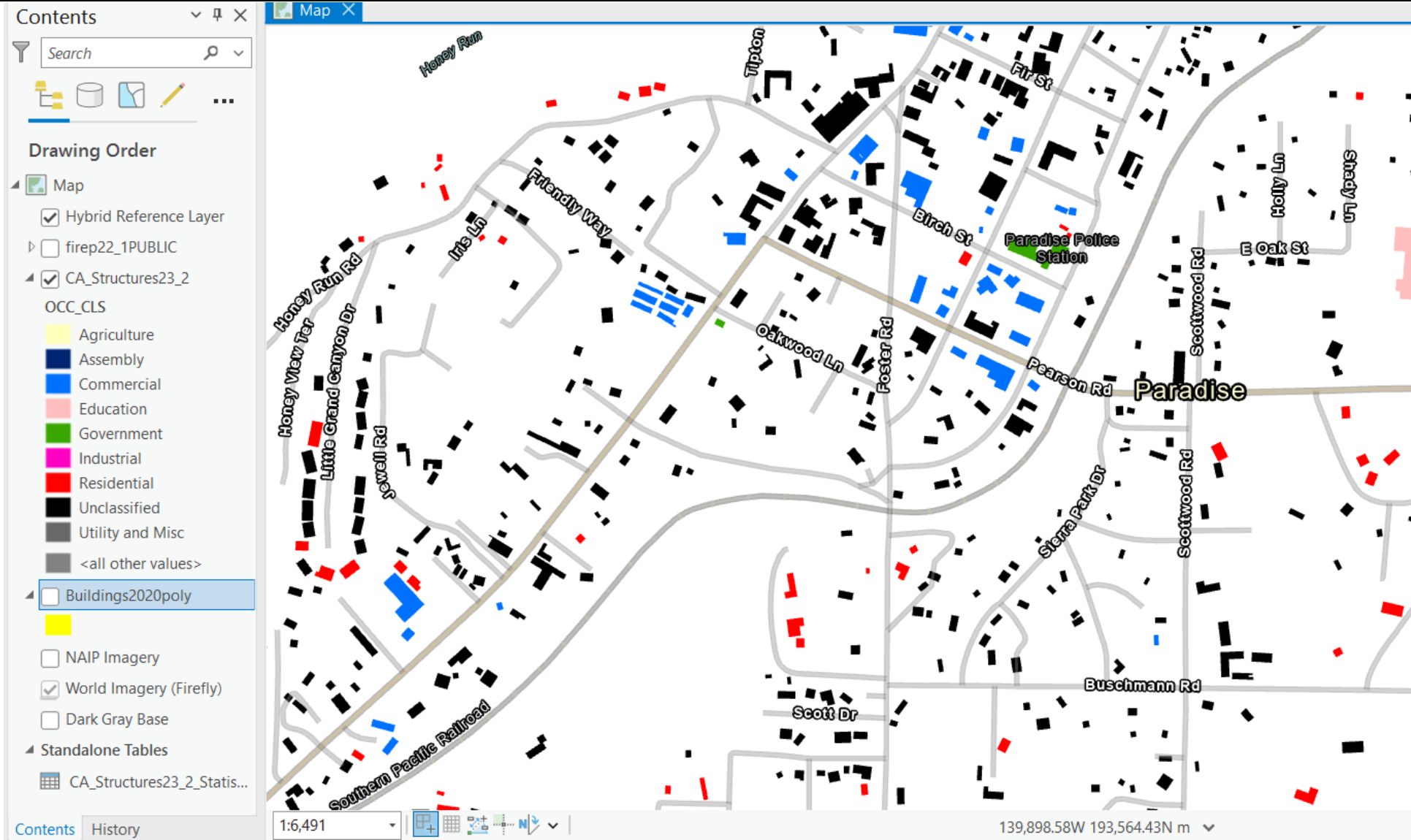
Structures USA (CA) Urban Area



# Camp Fire – Paradise (Nov 2018)

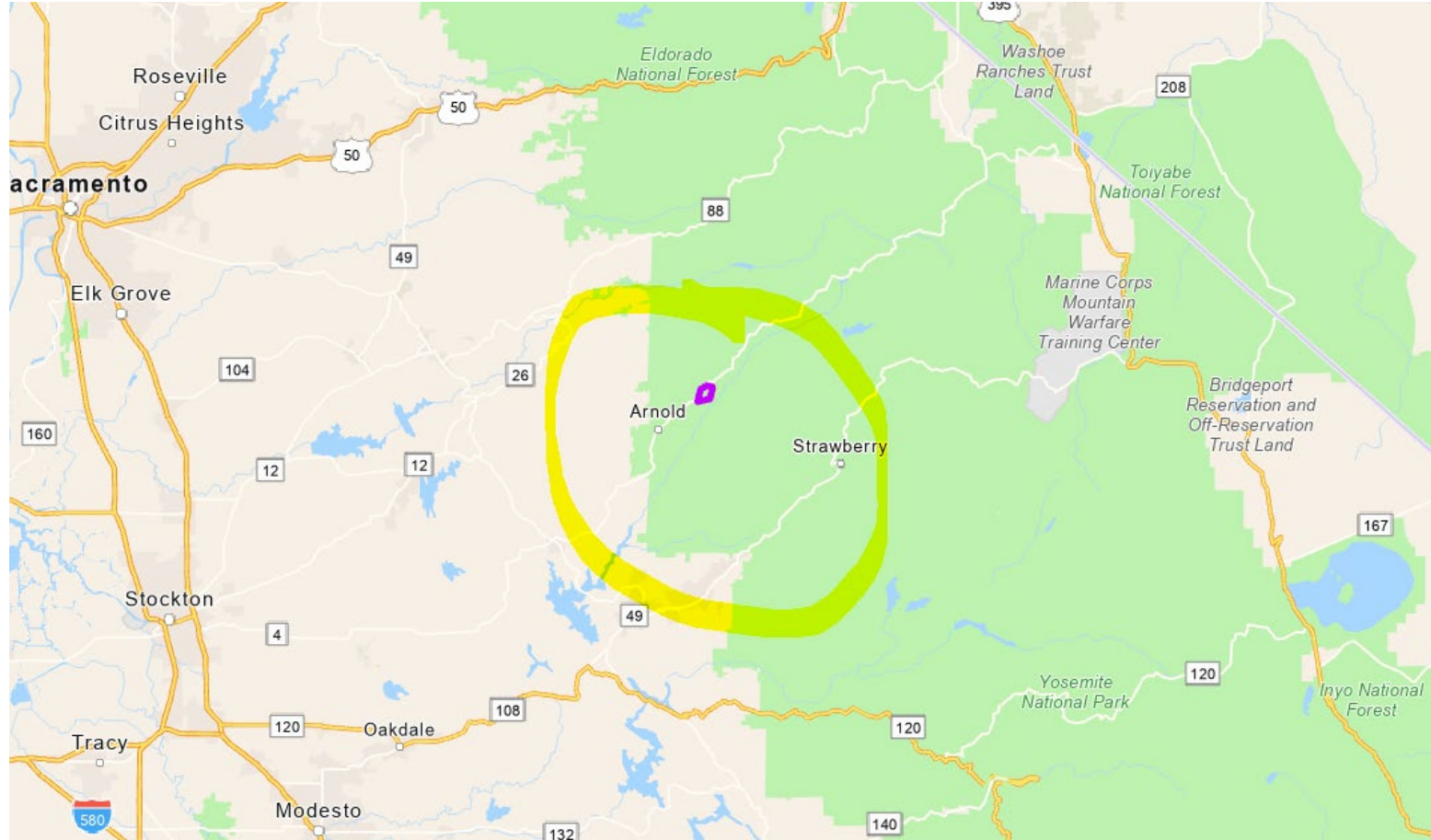


# Paradise Fire damaged homes = Unclassified

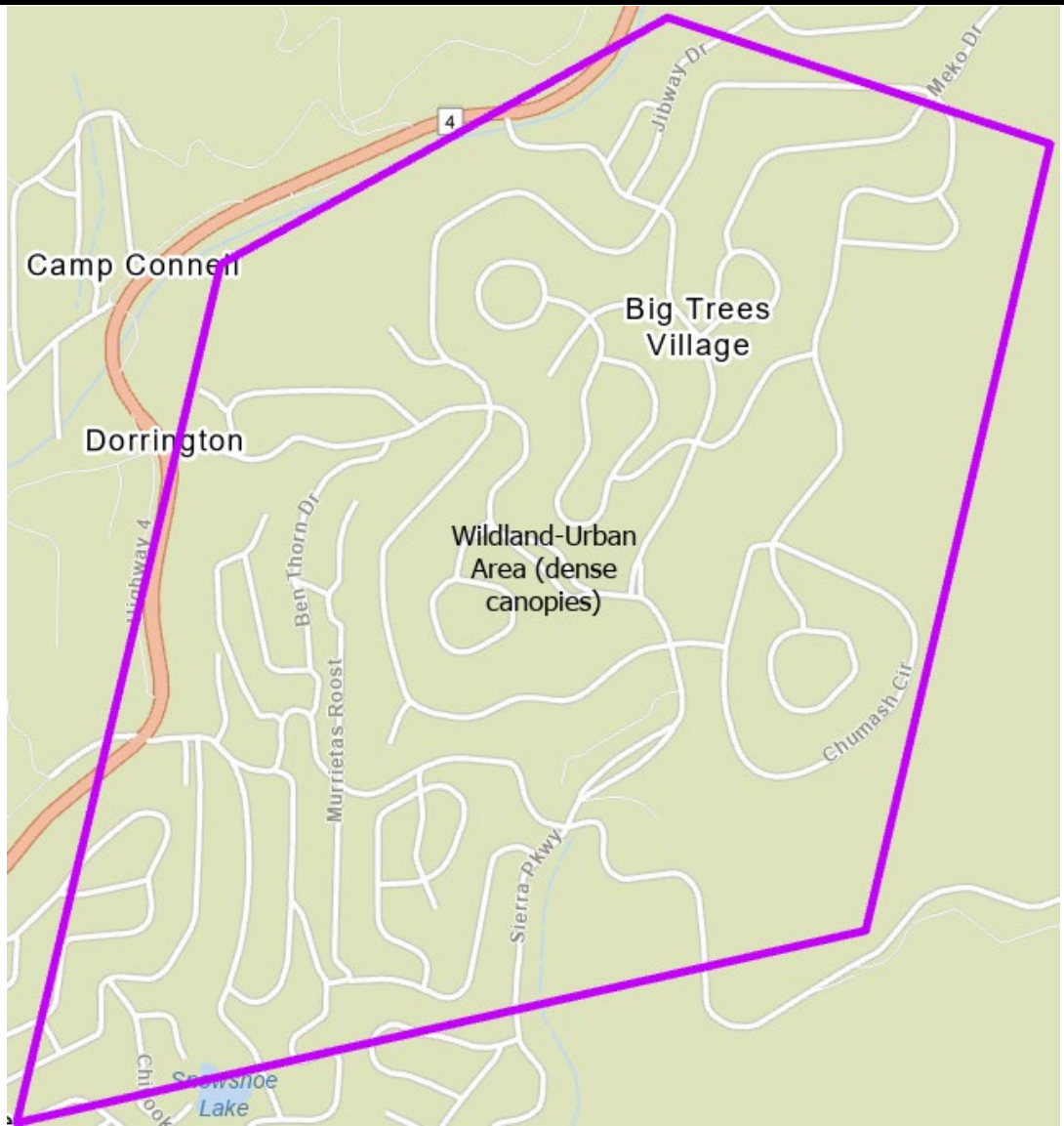




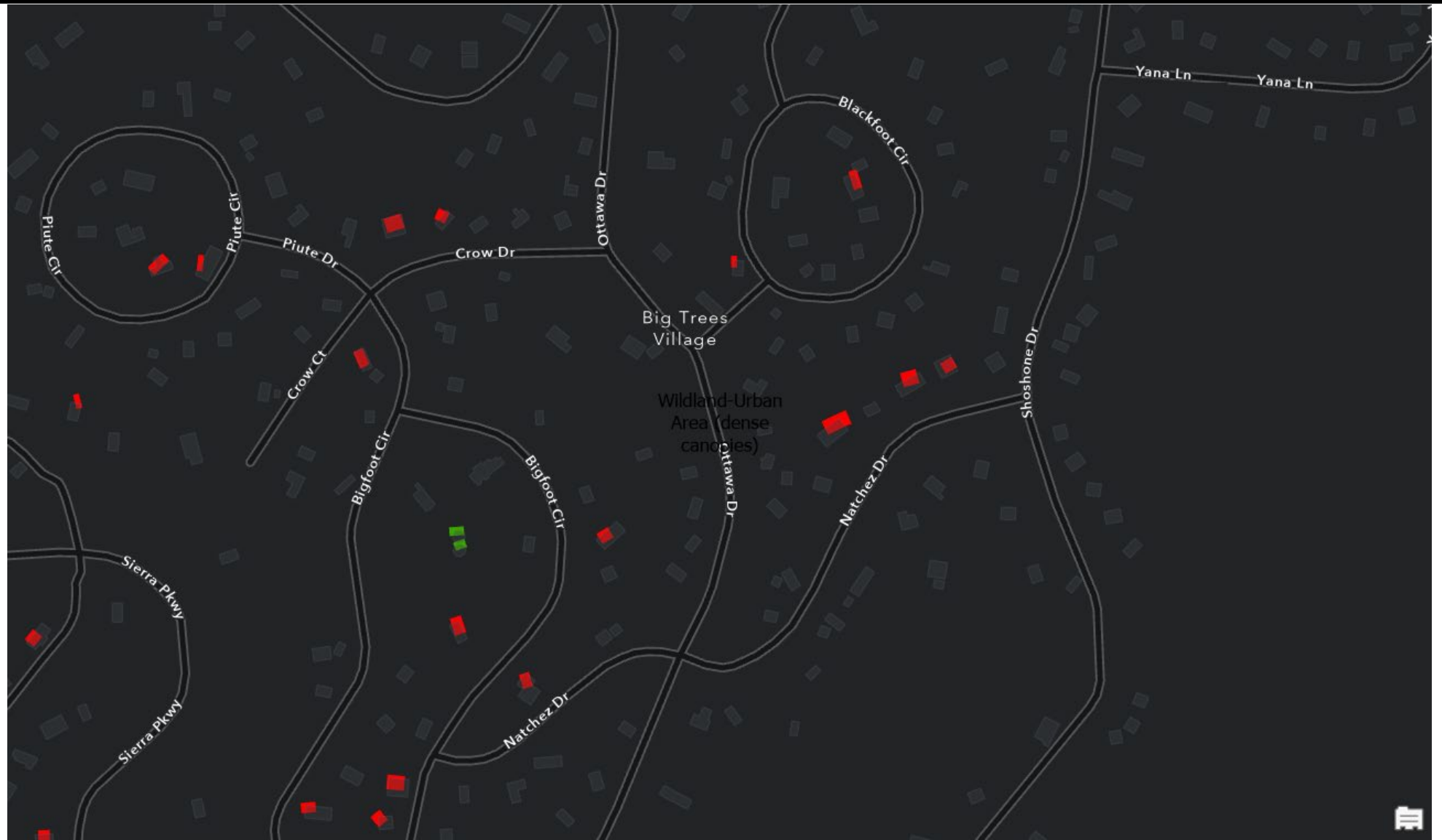
# Comparing datasets – dense overstory



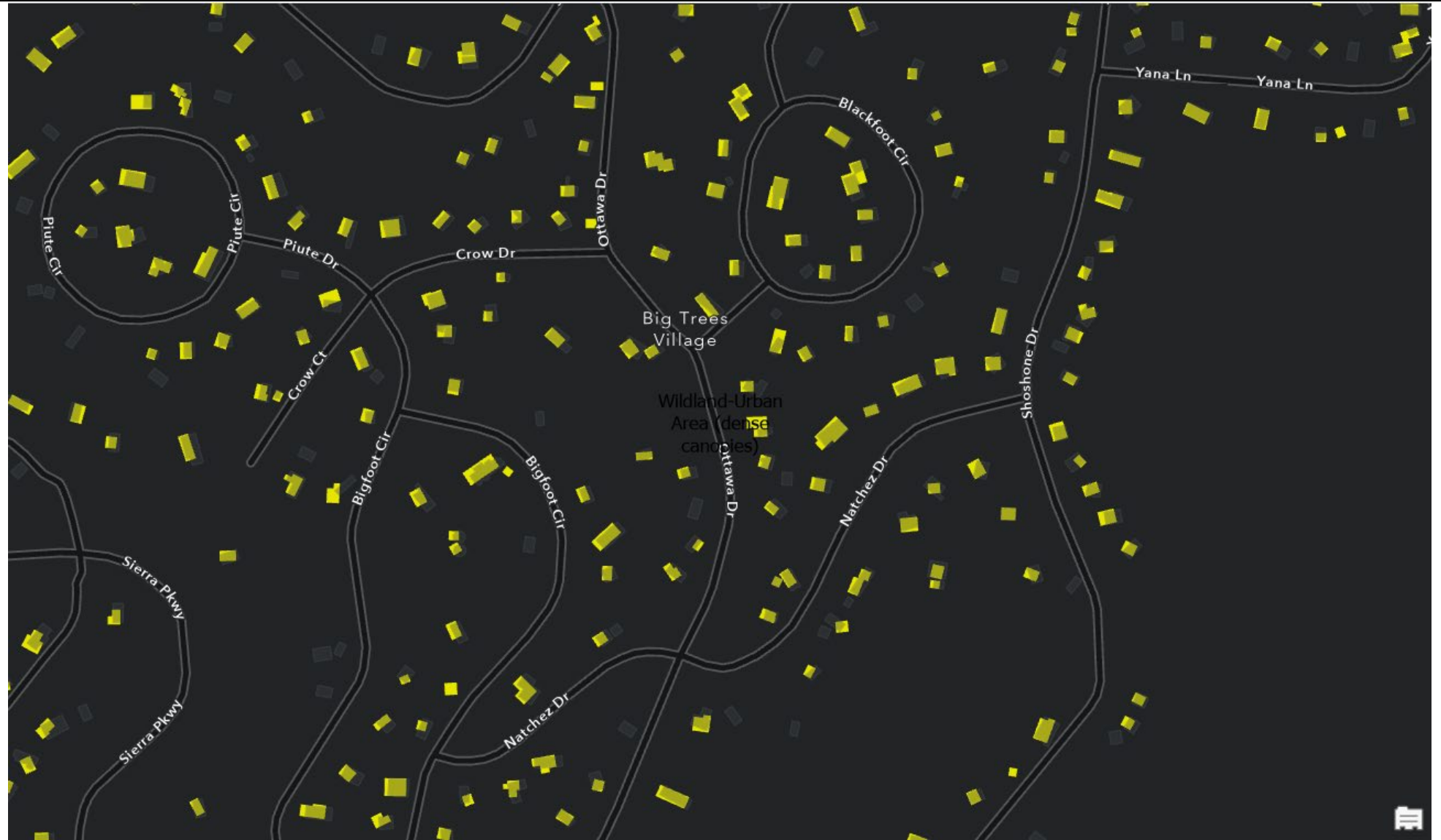
# Big Trees



# Structures USA

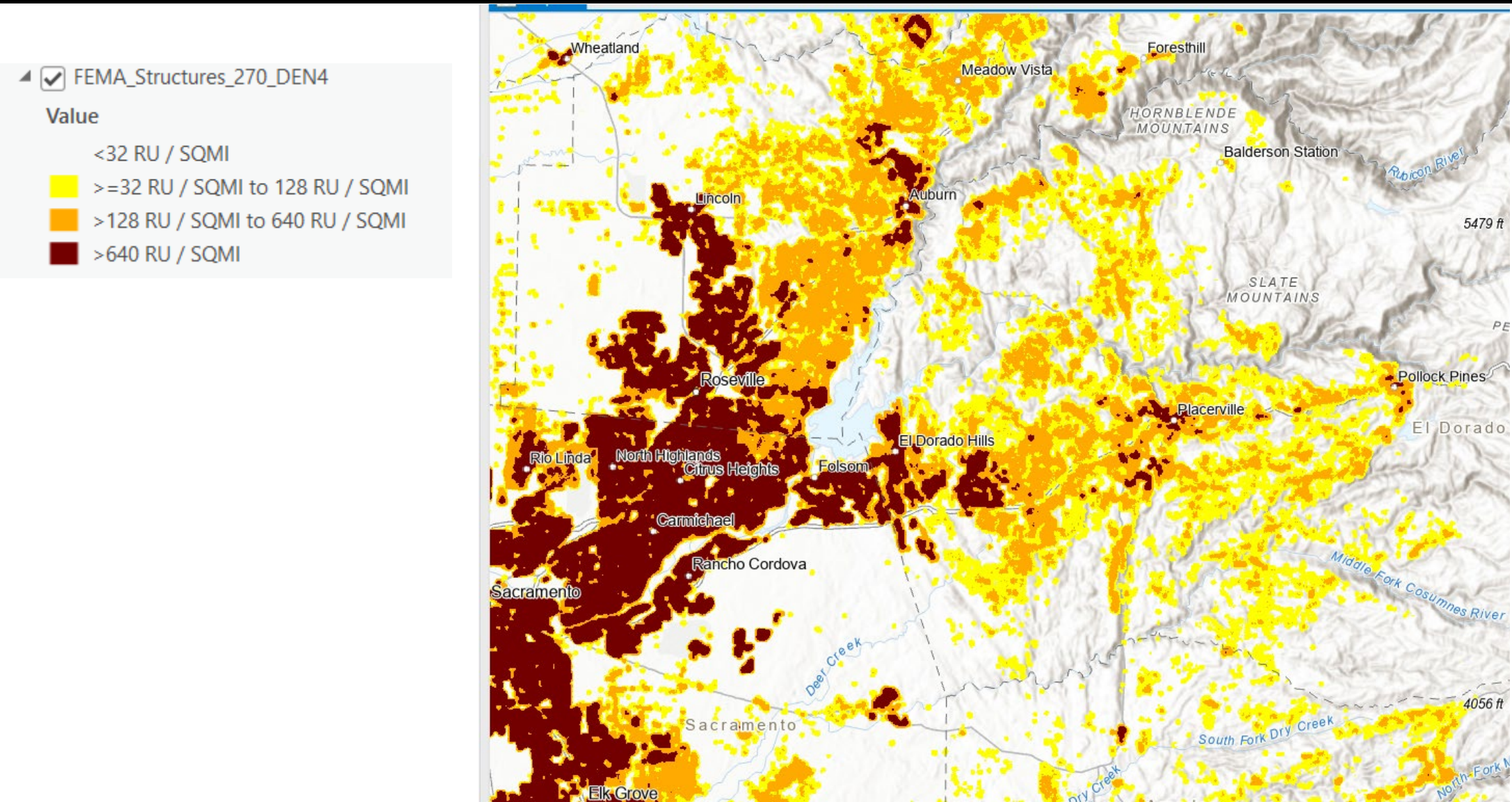


# MS Footprints

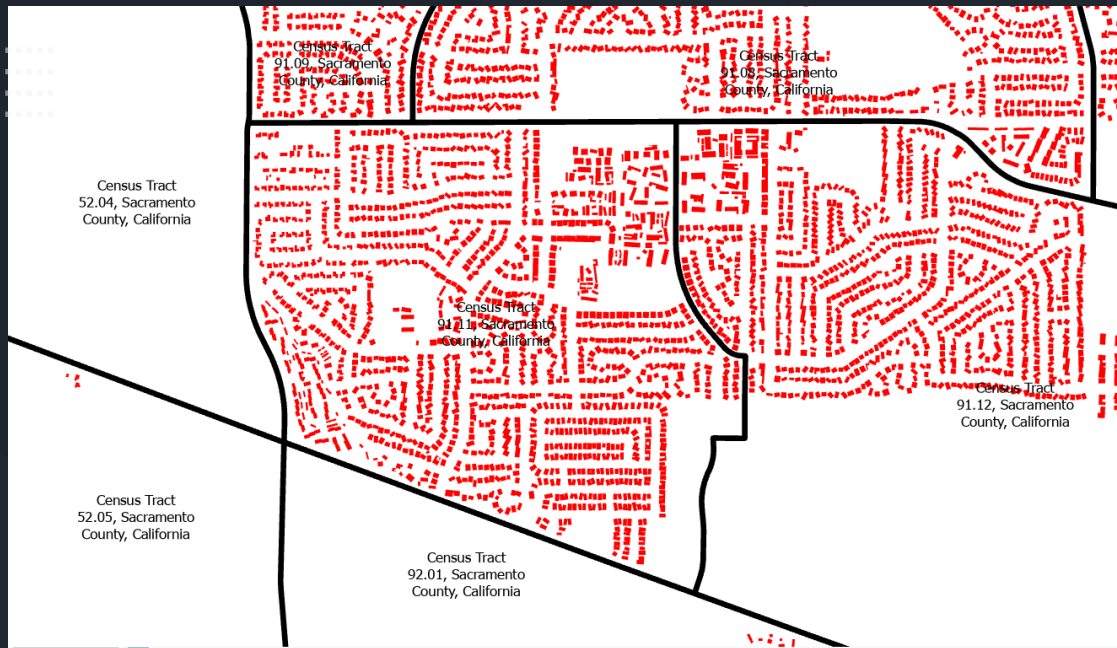




# WUI Characterization Input: Residential Density Maps



# Structures tell only part of the story (e.g. risk to households, populations...)



NAME	Census Tract 91.11, Sacramento County, California
POP2020	5670
PCTChildUnder5	4.3
PCT65Over	13.2
PCTPOVERTY	15.4
PCTNonEnglishLang	31.8
Non_White_Percent_1	54.568966
PCTDisability	21.9
CarOwner_Percent	2

# Mapping spatial patterns using Structures USA

- Pros
  - Identify residential structures
  - Updated regularly
  - Endorsed by FEMA
- Cons/Issues
  - Classification problems in rural areas
  - Does not reflect associated population metrics (e.g., housing units)
- Options
  - Enhance the data?
  - Apportion Block-level Census Housing Unit counts to Residential centroids (2020) and ACS for inter-census years?





Thank you!

- Jim Spero, Retired Annuitant
  - Fire and Resource Assessment Program
  - [jim.spero@fire.ca.gov](mailto:jim.spero@fire.ca.gov)
  - 916.337.1375





California Office of Data and Innovation (ODI) &  
California Department of Finance (DOF)

# California Building Footprints and their use in Small Area Population Estimates

Fennis Reed, Demographic Research Unit, DOF

Ian Rose, Data Services and Engineering, CalData, ODI

Brittany Allen, Data Services and Engineering, CalData, ODI

# Today's Agenda

**Intro to Small Areas**

**Building Footprint Dataset**

**Methodology**

**Case Study**

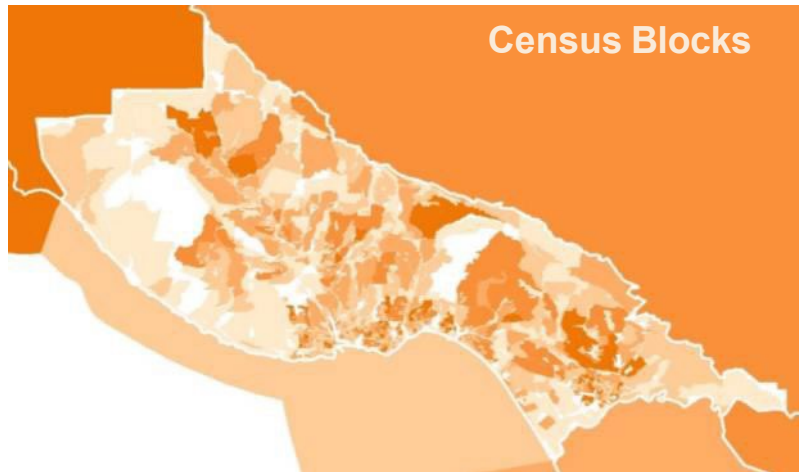
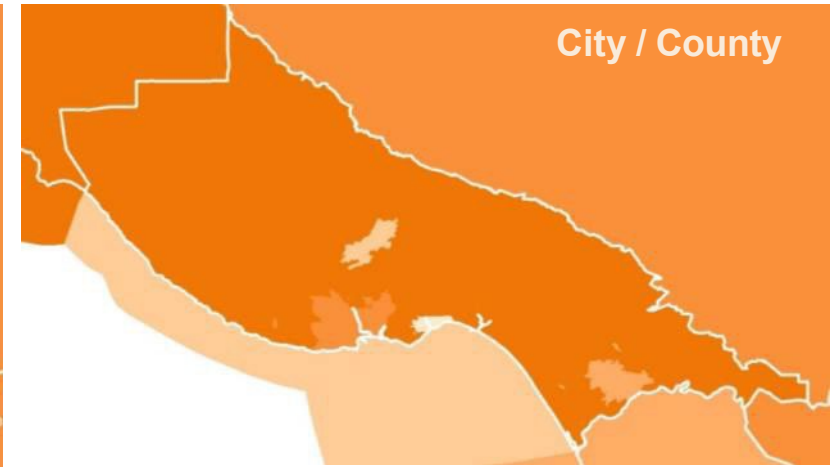
**Process Improvement**



# Small Area Estimation

- **Annual Estimates**
  - State, combined statistical area, County and City scale
- **Special Estimates:**
  - Unique jurisdictions ill-represented by aggregate estimates
    - Water districts
    - Library districts
    - Fire districts
    - Utility service areas

DOF x ODI



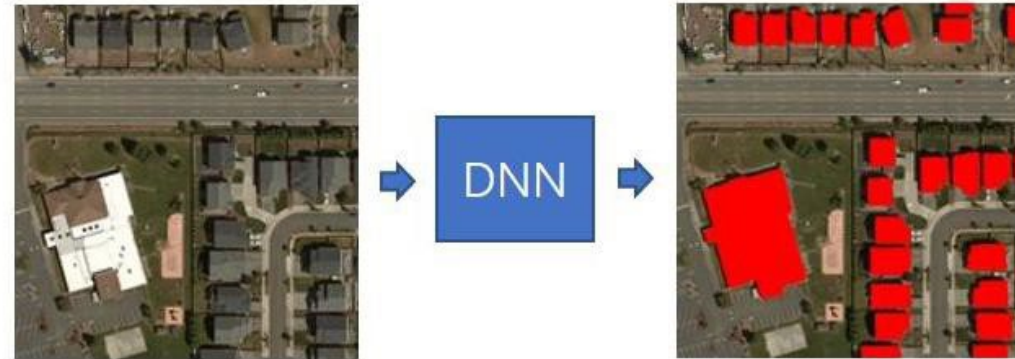
Essential Dataset

# Microsoft Building Footprints

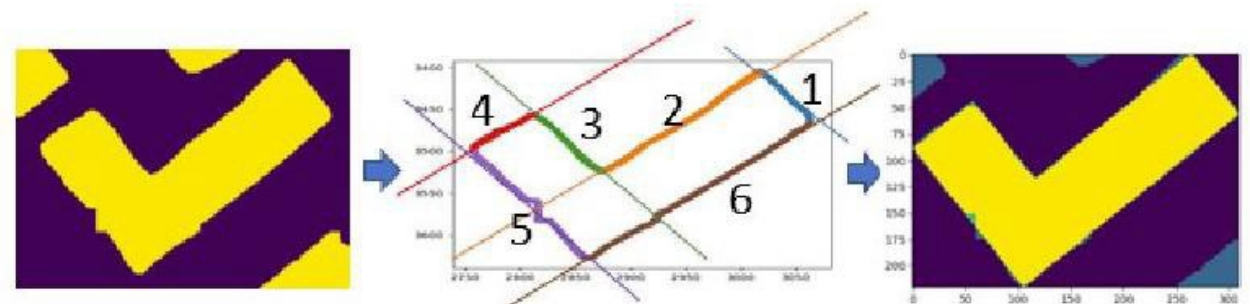
## Data source

- US and Global Footprints
- Machine Learning approach to footprint detection

Stage1: Semantic Segmentation



Stage 2: Polygonization



US Footprints



Global Footprints





Essential Dataset

# Microsoft Building Footprints

## Data source

- US and Global Footprints
- Machine Learning approach to footprint detection

## Challenges

- Global dataset receives updates
- Unintuitive and large downloads
- No index of footprints

US Footprints



Global Footprints





## Essential Dataset

# Microsoft Building Footprints

### Data source

- US and Global Footprints
- Machine Learning approach to footprint detection

### Challenges

- Global dataset receives updates
- Unintuitive and large downloads
- No index of footprints
- Errors of inclusion and exclusion

### Benefits

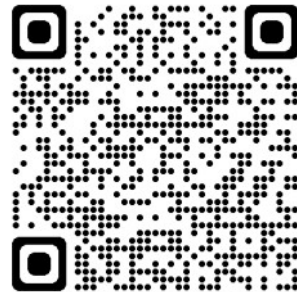
- Freely available
- Perform better than comparable projects

US Footprints

DOF x DPI



Global Footprints

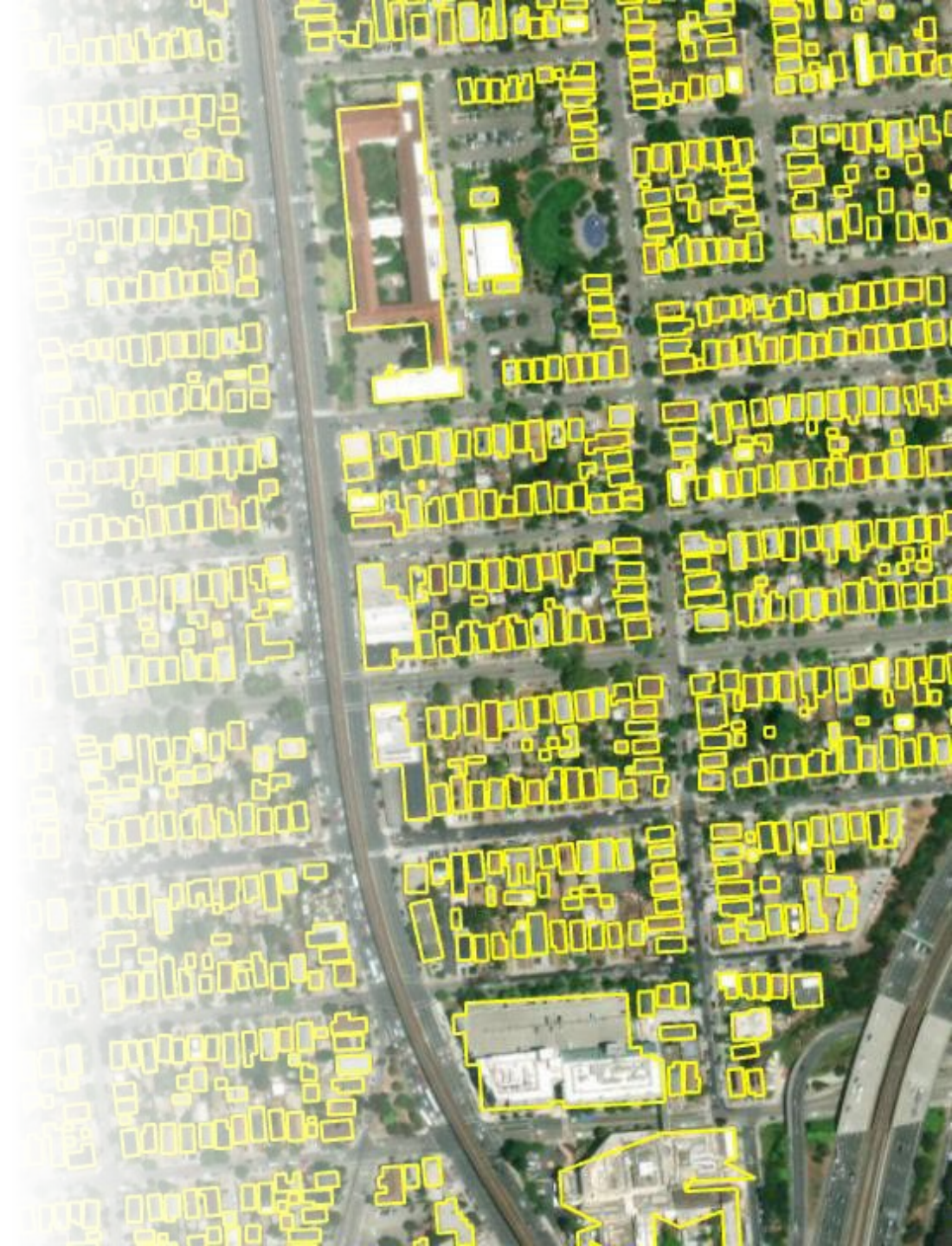




## Integration Problems with Microsoft Building Footprints

- ⊘ Hosted in non-intuitive platform as large files
- ⊘ Dataset updates are inefficient on local hardware
- ⊘ Revisions made with each new update are lost
- ⊘ Manual reconciliation with Census geometry
- ⊘ Time consuming parcel x footprint reconciliation

DOF x ODI



## An Innovative Solution

## California Building Footprints

- Collaboration with ODI CalData and Department of Finance
  - Data and Innovation Fund
    - Modern Data Stack Accelerator
- Same data, different ways to access:
  - URLs
  - Python-based workflow
  - ESRI ArcPro Toolbox

DOF x ODI

<https://cagov.github.io/data-infrastructure/data/footprints/>

Data Services and  
Infrastructure

## Building Footprints Dataset

## Global ML Building Footprints

County	GeoParquet (HTTPS)
Alameda	URL
Alpine	URL
Amador	URL

**Geoprocessing** v ↕ ✕

← Load Global Footprints from S3 →

**Parameters** Environments ?

\* **County Name**

**Temporary Directory**

📁

**Remove known errors of inclusion?**

```
import os
import geopandas

# Ensure S3 requests are anonymous, there is no need for AWS credentials here.
os.environ["AWS_NO_SIGN_REQUEST"] = "YES"

# Read GeoParquet using S3 URL
gdf = geopandas.read_parquet(
    "s3://dof-demographics-dev-us-west-2-public/"
    "global_ml_building_footprints/parquet/county_fips_003.parquet"
)

# Read Shapefile using HTTPS URL
gdf = geopandas.read_file(
    "https://dof-demographics-dev-us-west-2-public.s3.us-west-2.amazonaws.com/"
    "global_ml_building_footprints/shp/county_fips_003.zip"
)
```

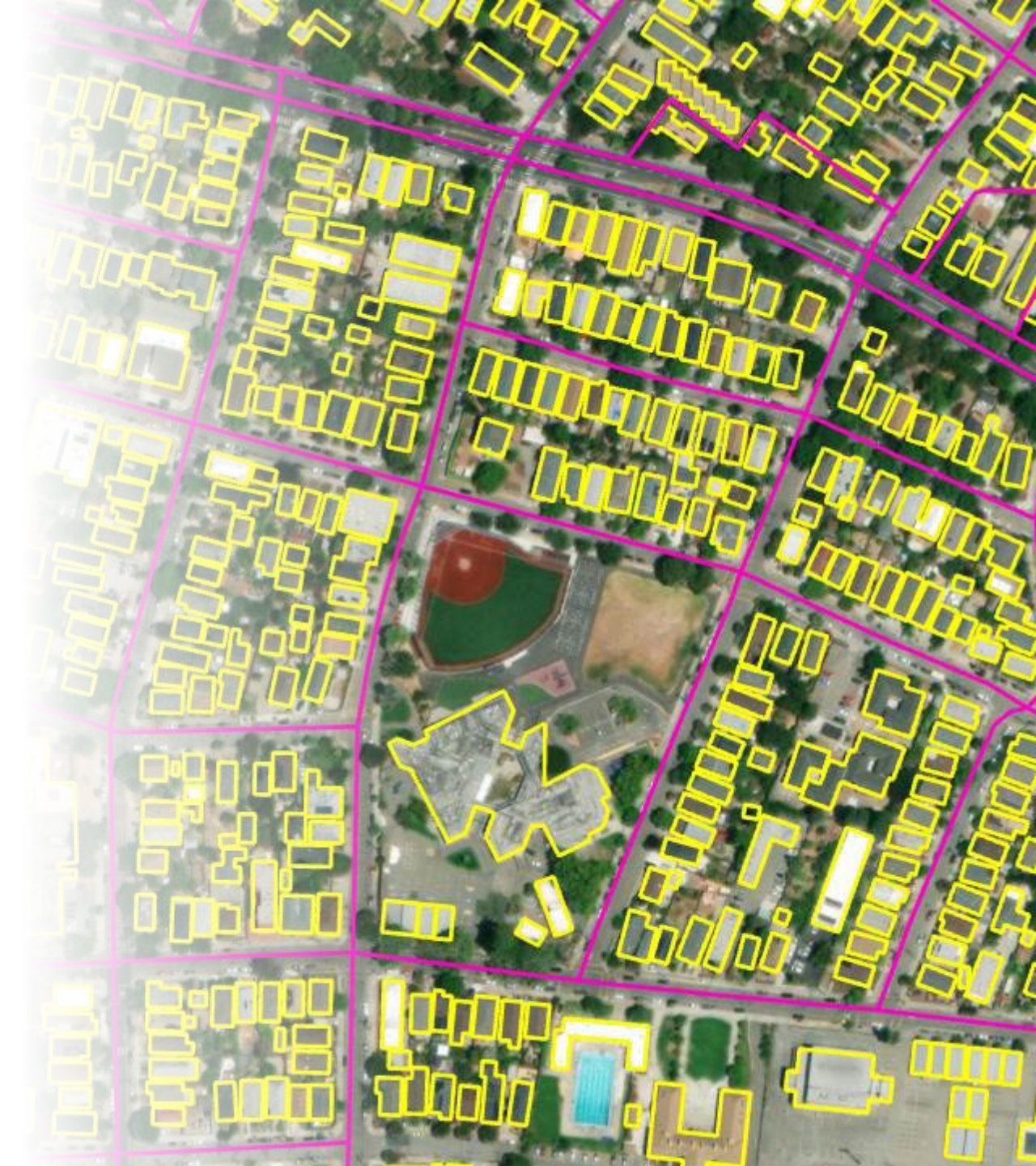


## An Innovative Solution

# California Building Footprints

- Collaboration with ODI CalData and Department of Finance
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- Same data, different ways to access:
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  - Python-based workflow
  - ESRI ArcPro Toolbox
- Added value
  - DOF x ODI Census TIGER lines

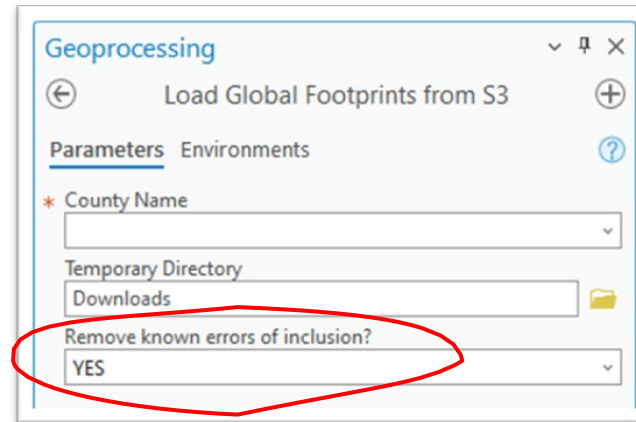
<https://cagov.github.io/data-infrastructure/data/footprints/>



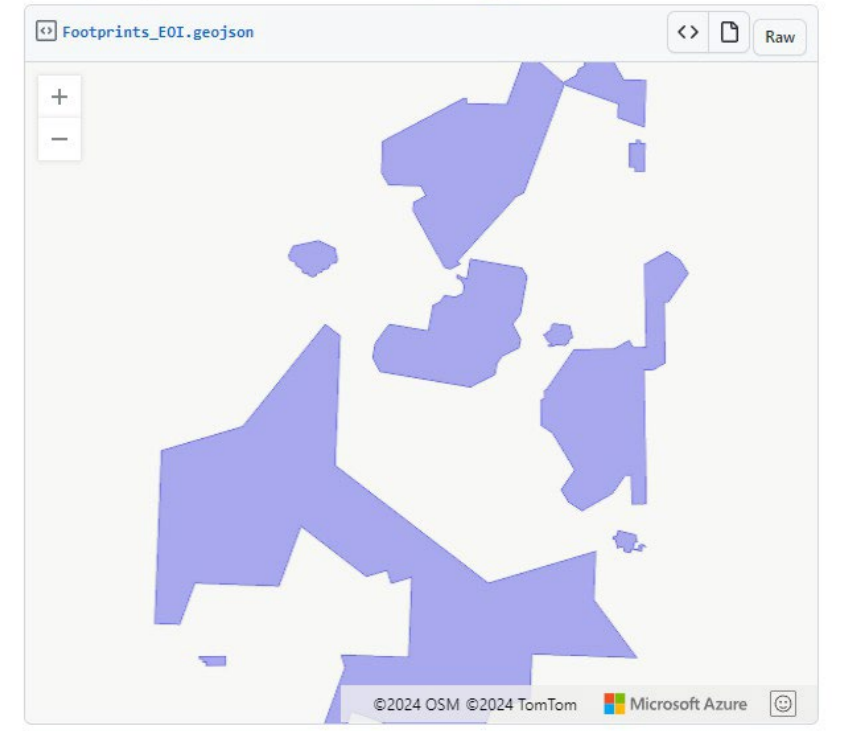
## An Innovative Solution

# California Building Footprints

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- Same data, different ways to access:
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  - Python-based workflow
  - ESRI ArcPro Toolbox
- Added value
  - DOF x ODI Census TIGER lines
  - Errors of Inclusion



A GeoJSON of select building footprints from the MS Global dataset identified as errors of inclusion, ie: non-footprint polygons wrongfully included. In support of the CalData and Department of Finance building footprints project. Additional errors may be reported at the following survey for inclusion in this GeoJSON. <https://arcgis/1qmXDC>

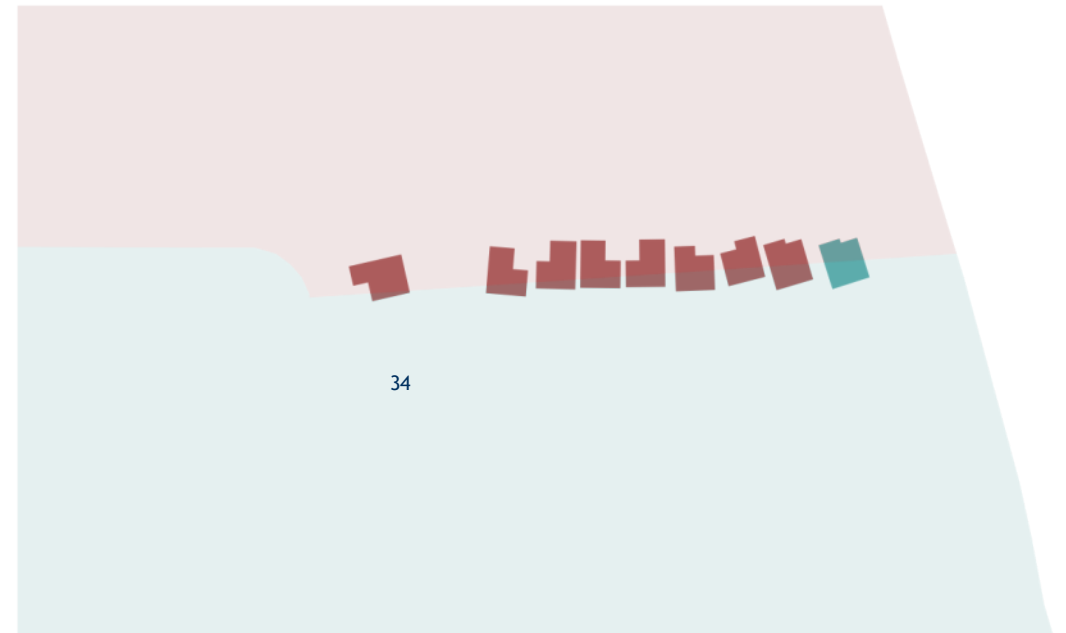


<https://cagov.github.io/data-infrastructure/data/footprints/>

### Joining with Census TIGER data

- Original footprint dataset doesn't have much detail or metadata, it's just a big list of shapes
- As part of our data pipeline, we partition by county and enrich with Census TIGER shapes
- If a footprint intersects more than one geometry, assign it to the geometry with a bigger overlap
- Allows for more efficient reads of the data:
  - Only read the counties you need
  - Only read the columns you need\*
  - Only read the census geometries you need\*

DOF x ODI



\* GeoParquet only

## File formats (everyone's favorite topic)

- Stored in a public AWS S3 bucket, anyone can download them
  - Cheap, reliable, fast
  - API access as well as HTTP download URLs
- Delivered in both GeoParquet and zipped Shapefile formats

	GeoJSON (original)	Zipped Shapefile	GeoParquet
Efficient storage			
Cloud-friendly			
Sensible data types			
Universally supported			



# Method Overview

- Conceptual framework
- Foundational model
- Adapted model



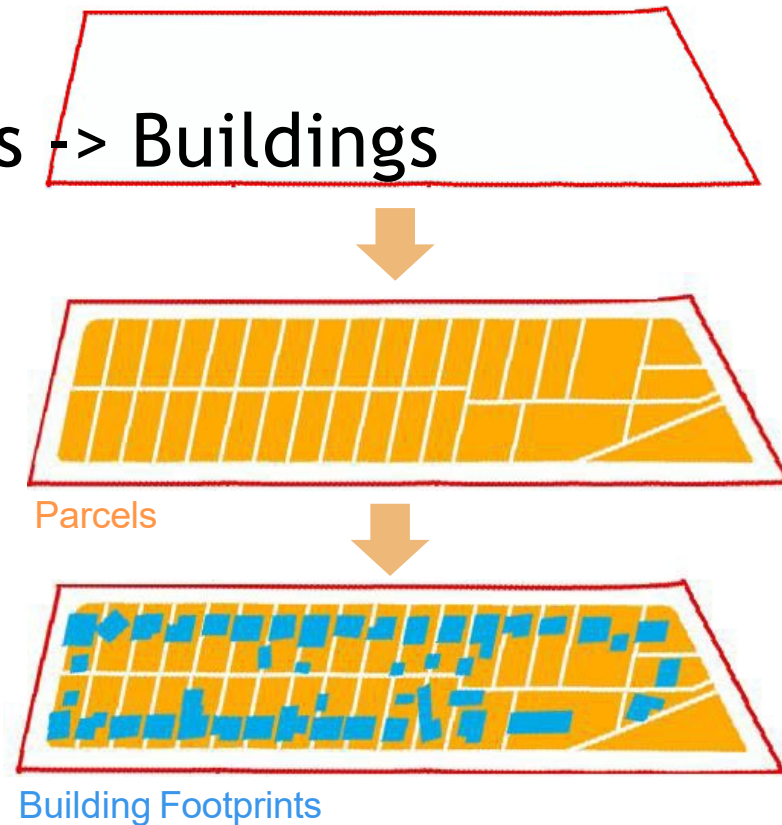
# Dasymetric Mapping

**Definition:** a method for refining coarse data with ancillary information about the distribution of the variable.

- Assumption:
- County -> Blocks -> Parcels -> Buildings
- Problem:
- Incongruent geometry

DOF x ODI

**Expectation:**



**Reality:**



# Dasymetric Mapping

## Assumption:

County -> Blocks -> Parcels -> Buildings

## Problem:

Incongruent geometry

Previously normalized for the whole state

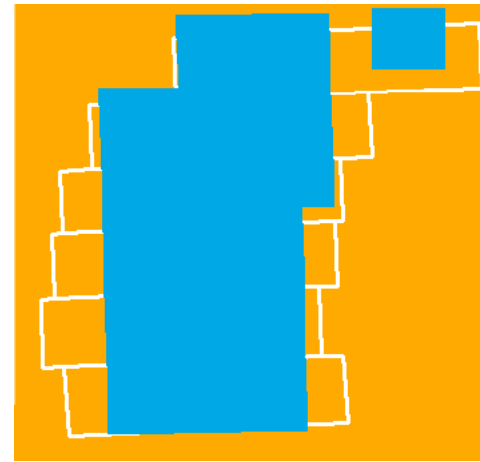
## Solution:

Toolbox to enable the integration of census, parcel, and footprint information on the fly

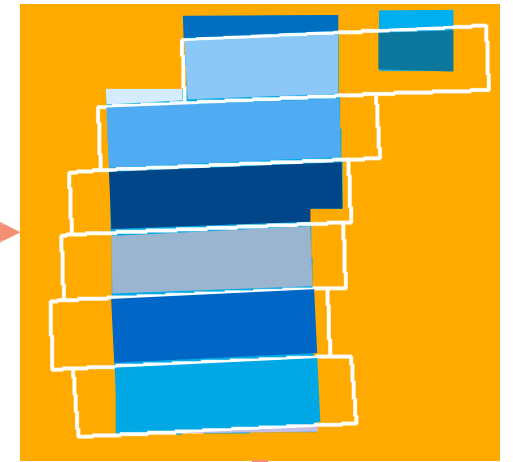
- Threshold parameters
- Number of intersections
- Minimum area
- Percent contribution

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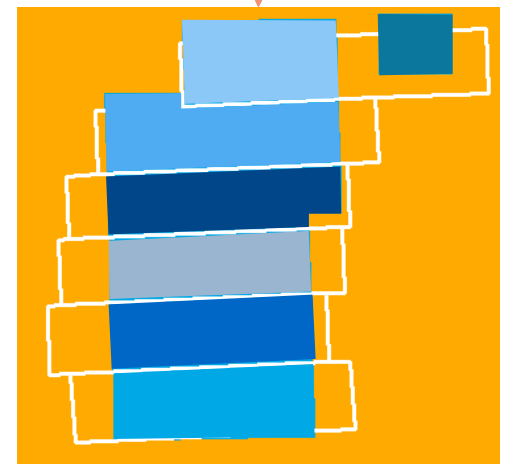
Building Footprints + Parcels



Union



Dissolve



## Cadastral Expert Dasymetric System (CEDS)

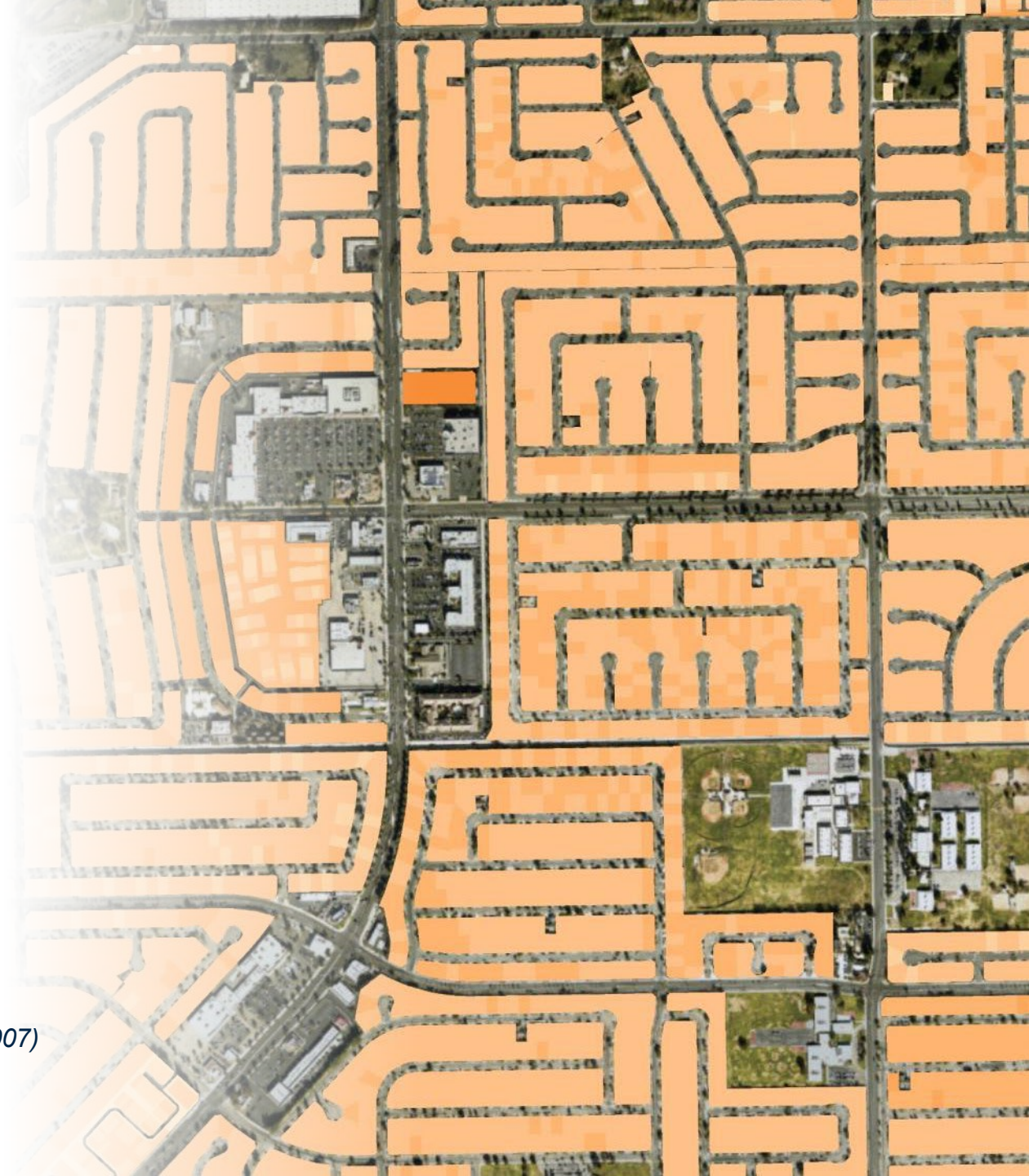
### Foundational Method

- Top-down, dasymetric population model
- Distributes larger unit down to Parcels by:
  - Residential area
  - Residential units
- Selects minimal difference to finest unit
- Applies method to larger unit

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*Florida has great data!*

(Strode, G., V. Mesev, J. Maantay. 2018, Maantay, J.A., A.R. Marko, C. Hermann. 2007)





## Cadastral Expert Dasymetric System (CEDS)

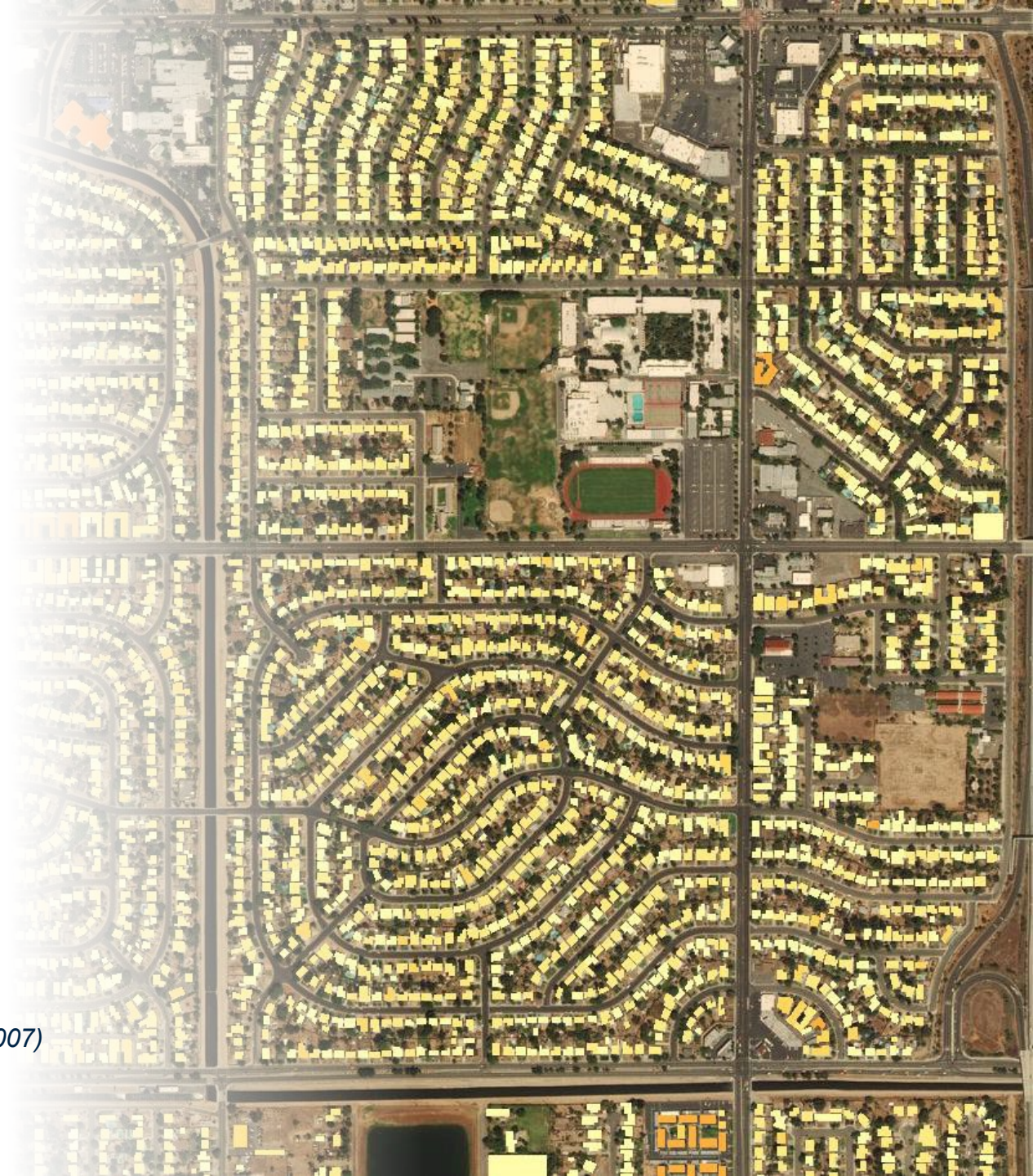
### Adapted Method

#### Additions to the Model

- American Community Survey inputs at different scales
- Building footprint mask
- Specific group quarters allocation
- Disaster response incorporation
- City / County adjustment

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*(Strode, G., V. Mesev, J. Maantay. 2018, Maantay, J.A., A.R. Marko, C. Hermann. 2007)*





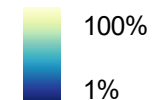
# Cadastral Expert Dasymetric System (CEDS)

## Expanded Variable List

- Residential units
- Residential area
- Building footprint area
- Parcel area
- Bedrooms
- Estimate of Housing Unit Density
  
- Incomplete coverage
- Augment units and area
  - HCD APR
  - Housing Unit Survey
  - Assessor's use codes



Percent of Residential Parcels

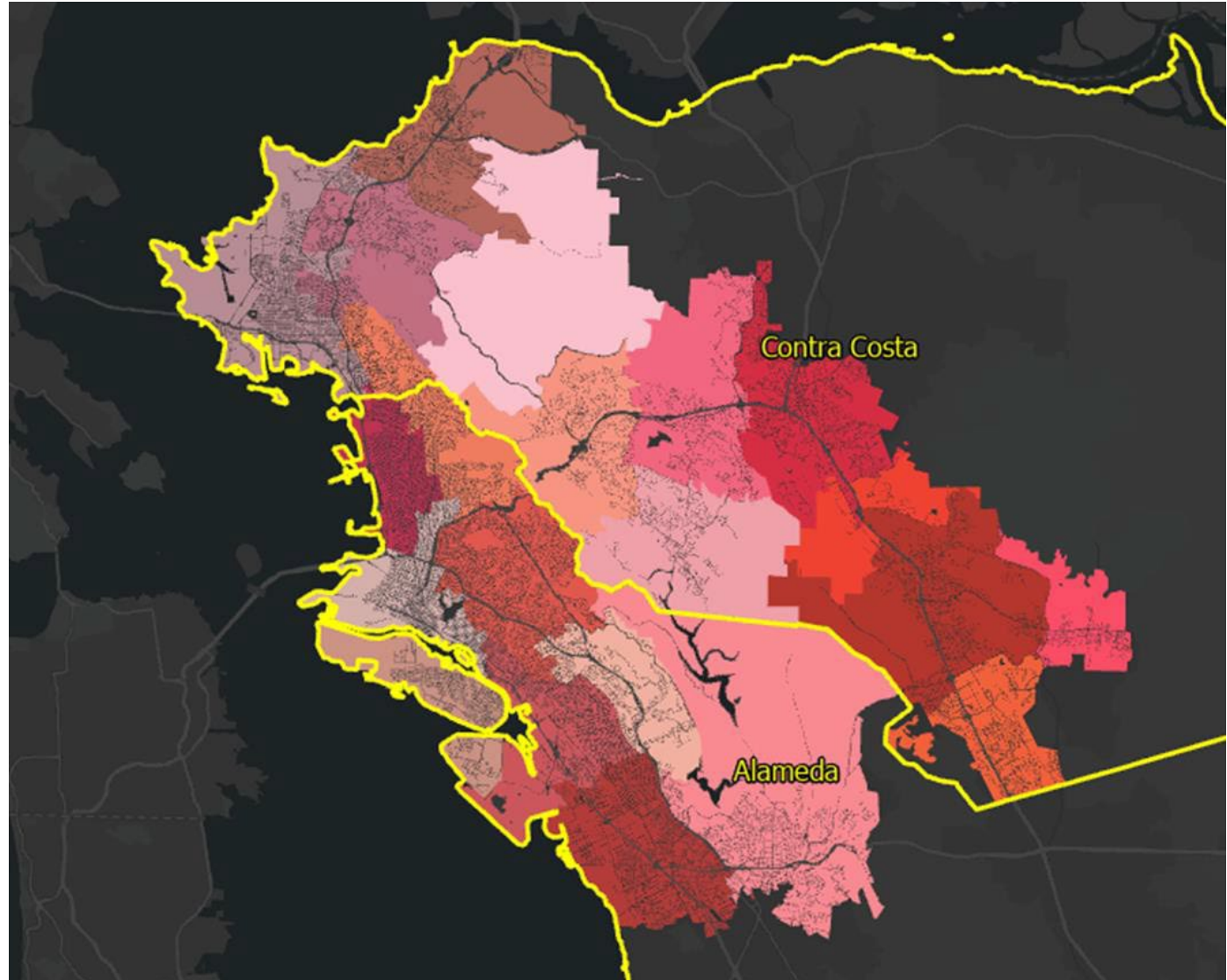


## Case Study

# East Bay Municipal Utility District, 2023

- Water demand projections
- 21 unique zones
  - Intersects
    - 2 Counties

DOF x ODI

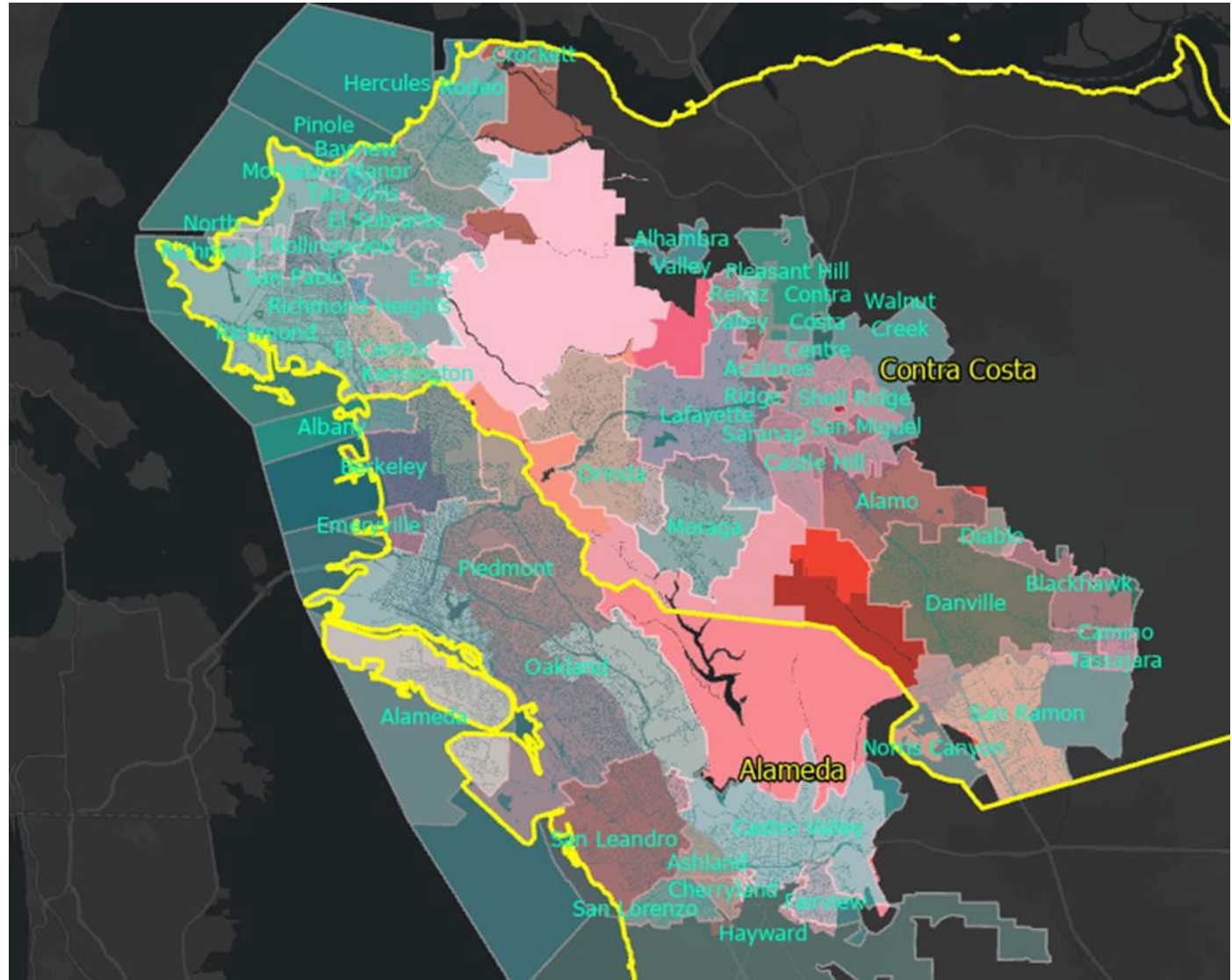


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DOF x ODI

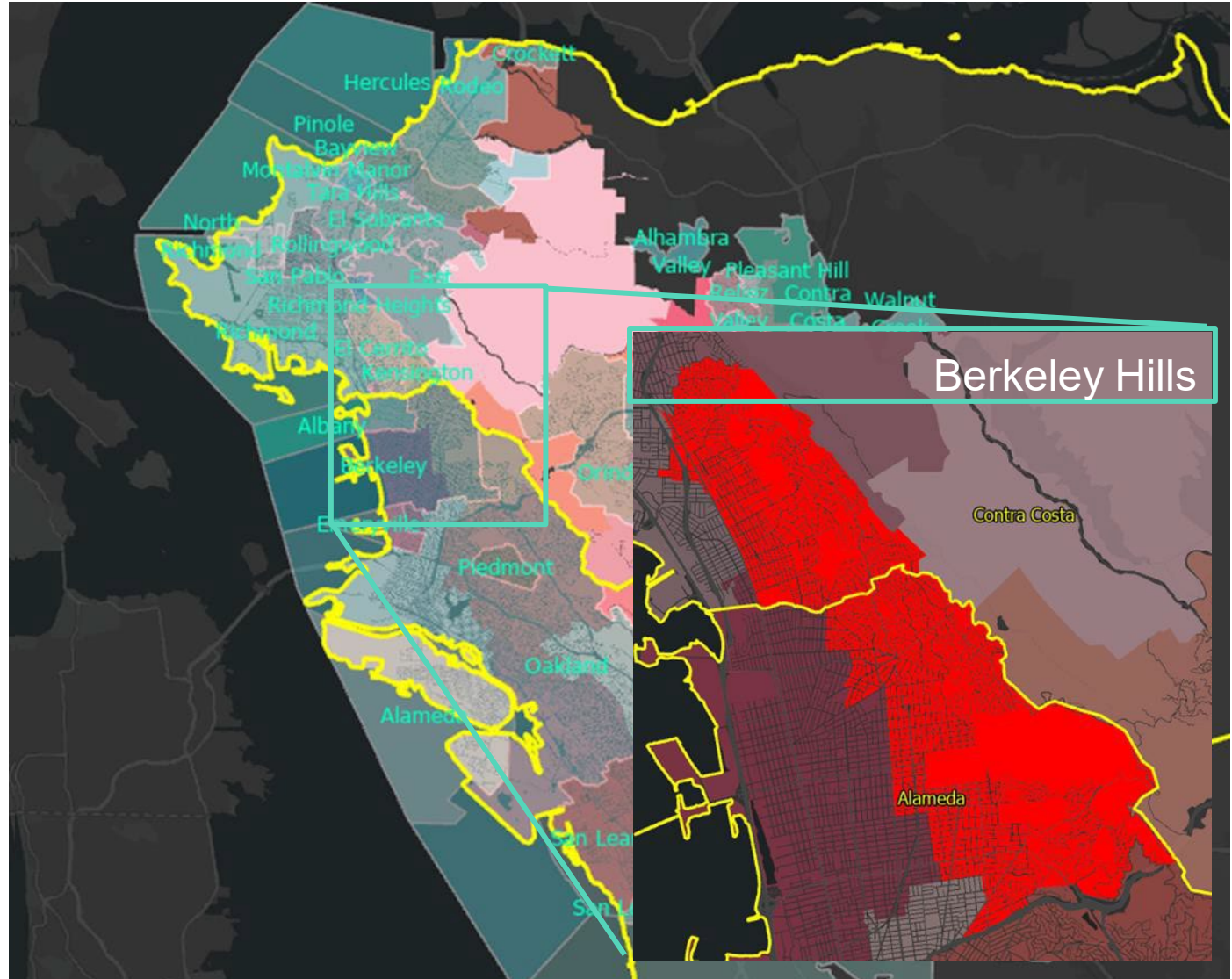




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DOF x ODI

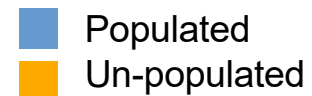
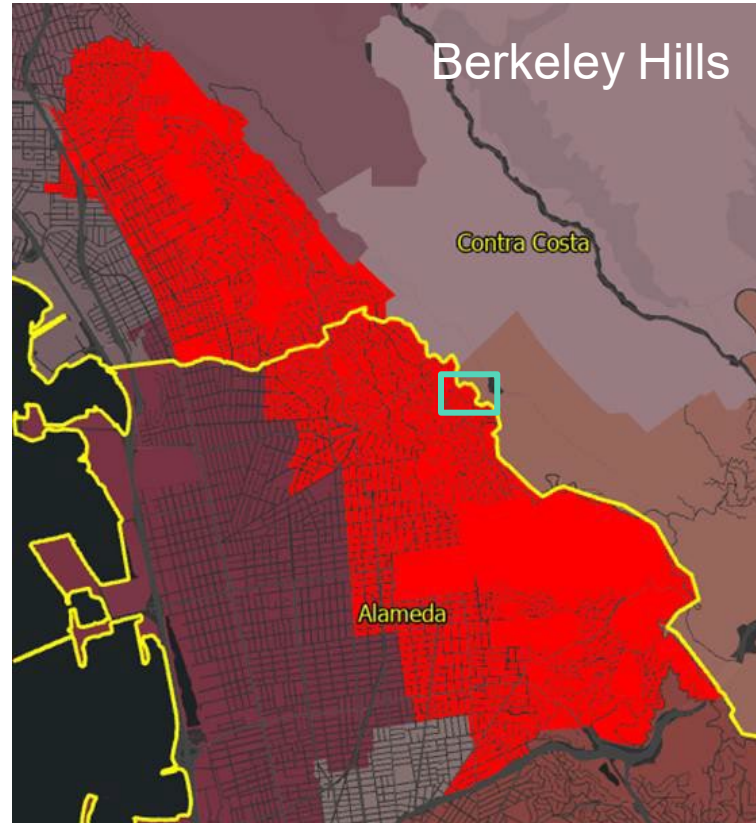


## Case Study

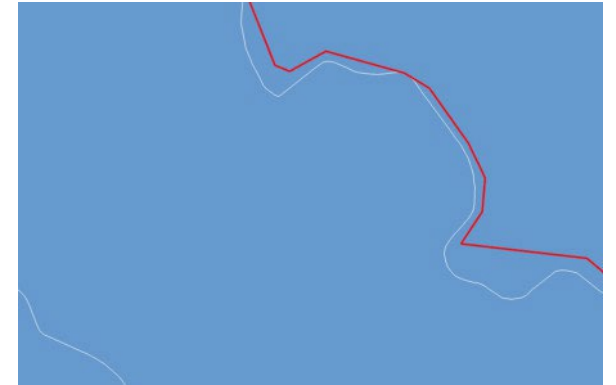
# East Bay Municipal Utility District, 2023

- Water demand projections
- 21 unique zones
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    - 2 Counties
    - 48 Incorporated Cities
- ACS Housing Range
  - 33,139 - 51,695

DOF x ODI



BLOCK GROUPS

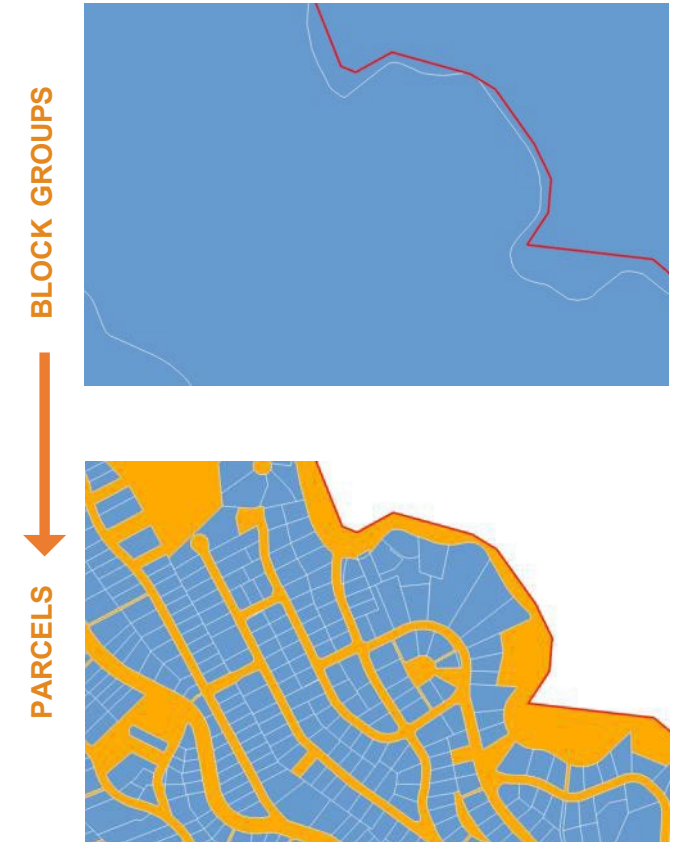
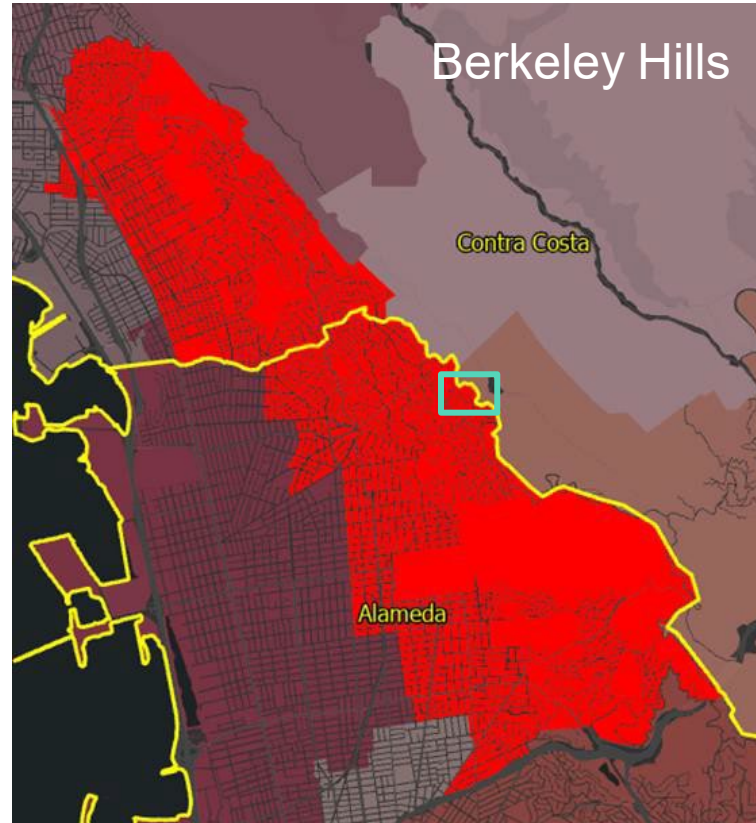


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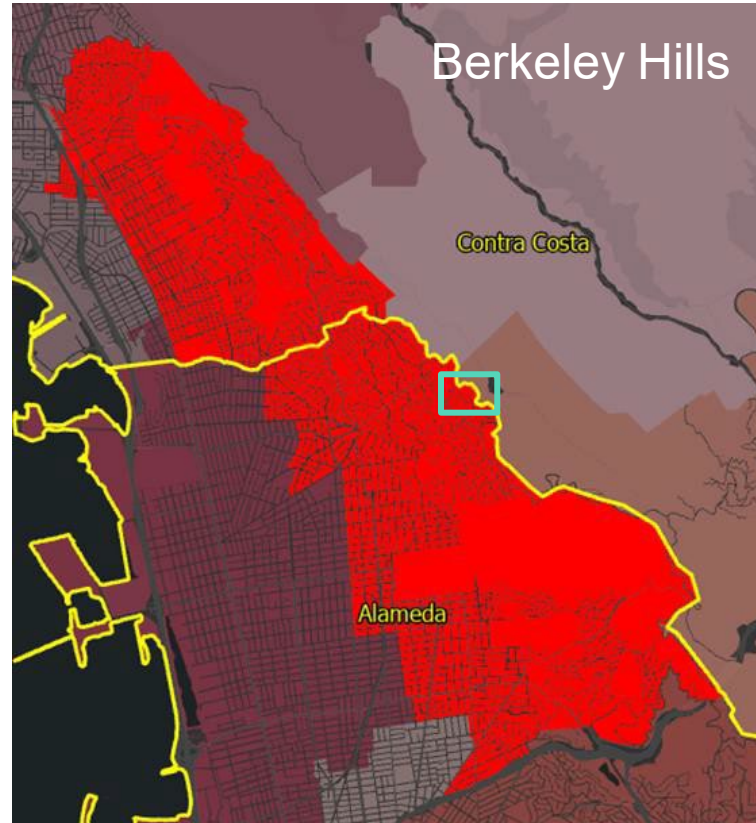
DOF x ODI



## Case Study

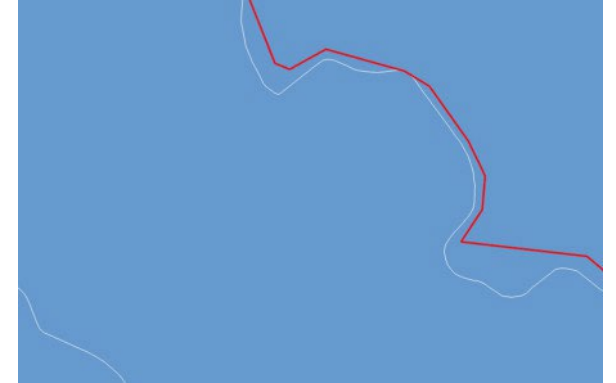
# East Bay Municipal Utility District, 2023

- Water demand projections
- 21 unique zones
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    - 2 Counties
    - 48 Incorporated Cities
- ACS Housing Range
  - 33,139 - 51,695
- CEDA Estimate: 43,509
  - Alameda: 30,708
  - DOF x ODI Contra Costa: 12,801
    - Richmond: 337



■ Populated  
■ Un-populated

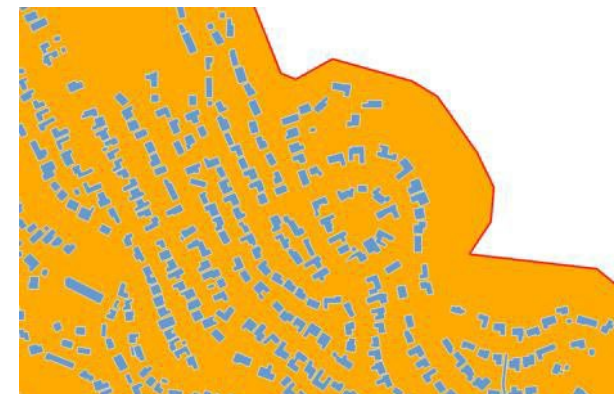
BLOCK GROUPS



PARCELS



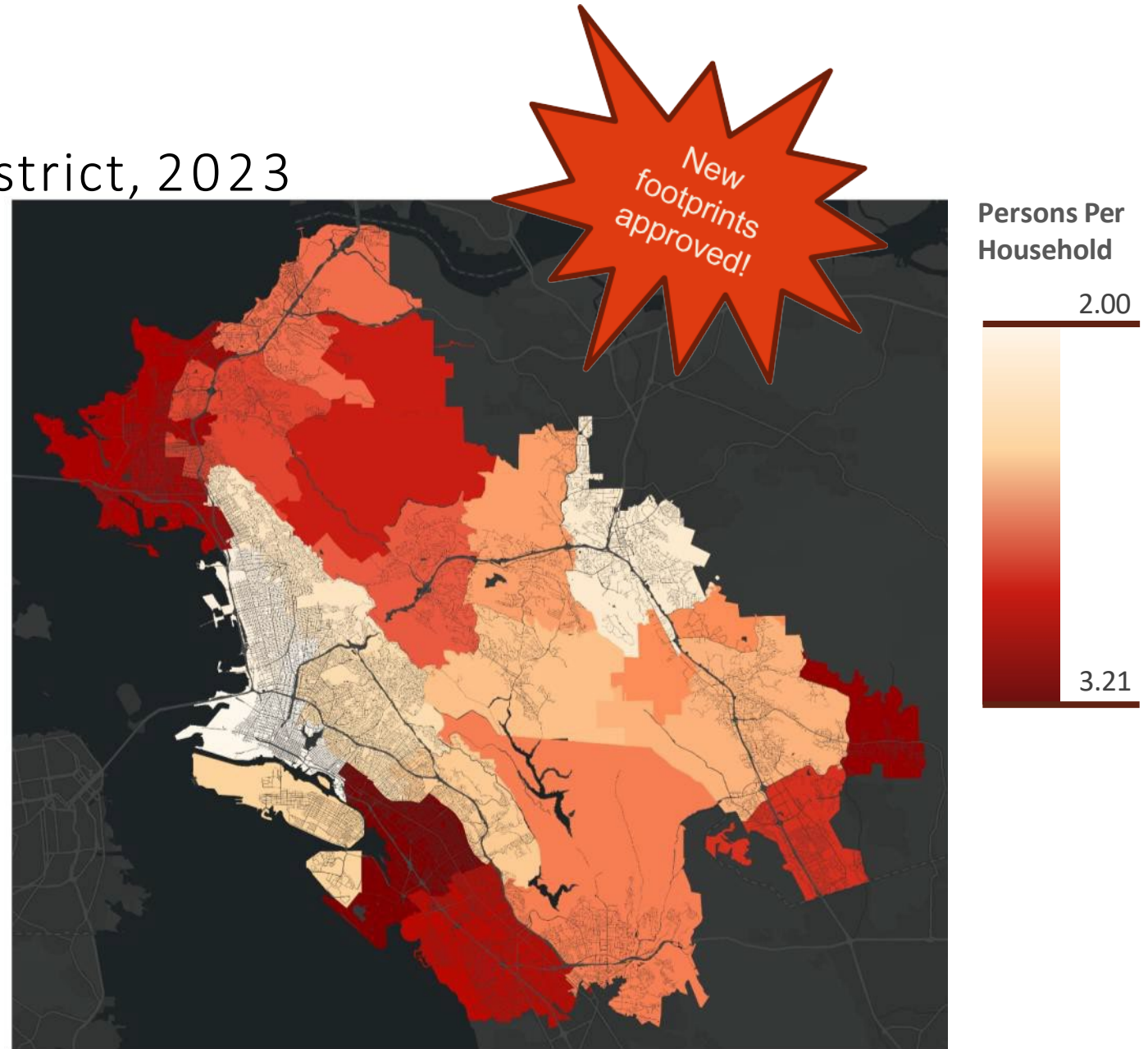
BUILDING FOOTPRINTS





## Case Study

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- Water demand projections
- 21 unique zones
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- ACS Housing Range
  - 33,139 - 51,695
- CEDS Estimate: 43,509
  - Alameda: 30,708
  - Contra Costa: 12,801
  - Richmond: 337
- Unique PPH and housing for each zone





## Integration Solutions for

# Microsoft Building Footprints

❌ Hosted in non-intuitive platform as large files

✅ Publicly available for granular download with multiple accessible methods

❌ Dataset updates are inefficient on local hardware

✅ Periodic automated update schedule in the cloud

❌ Revisions made with each new update are lost

✅ Previous revisions can be retained between updates

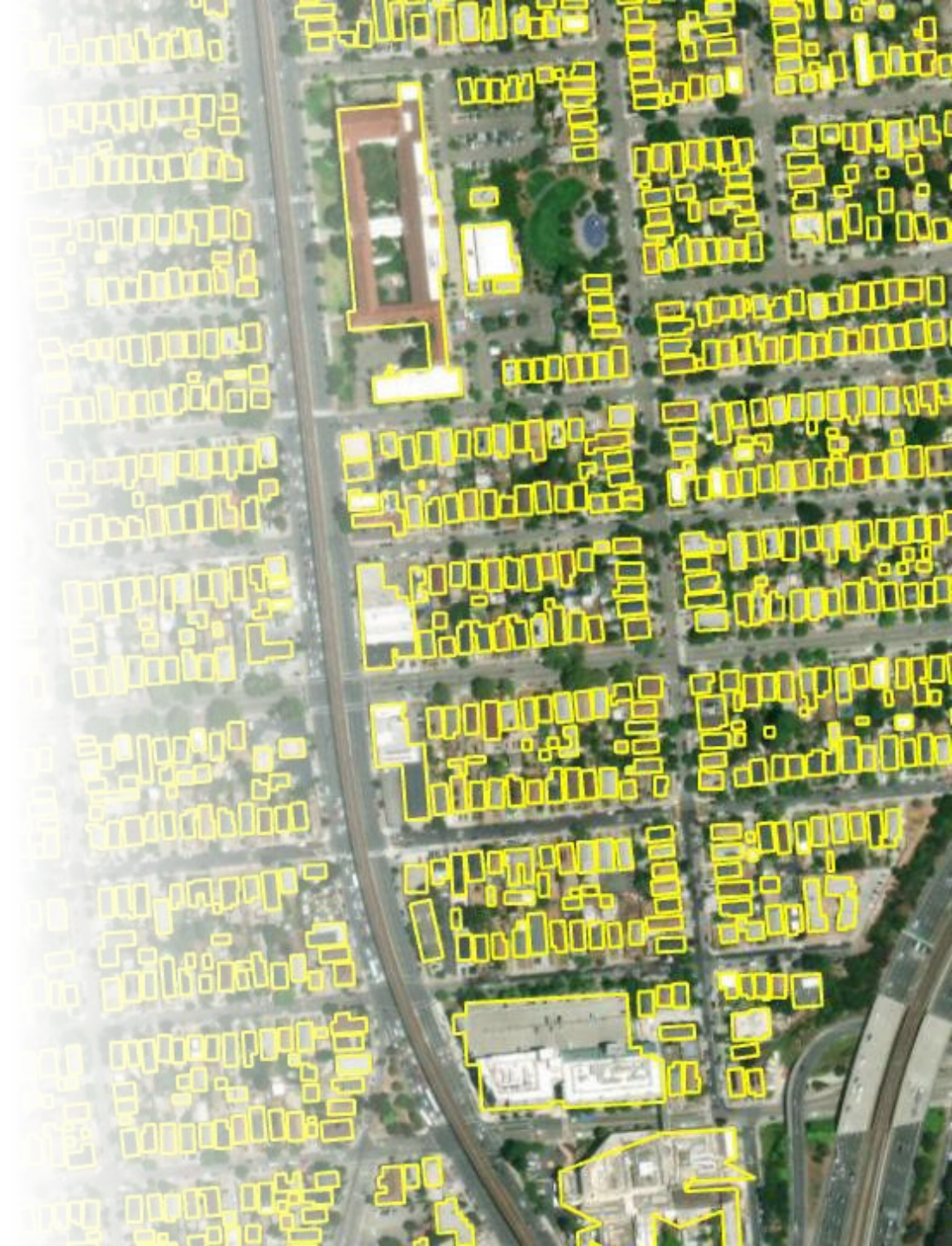
❌ Manual reconciliation with Census geometry

✅ Calculated automatically with each update

DOF x ODI

❌ Time consuming parcel x footprint reconciliation

✅ Highly customizable and time efficient





# Conclusion

- Footprints are easy to access and use
- Empowers integration with existing dasymetric methods
- Estimates are constantly improving with emerging data



# Thank you!

## California Demographic Research Unit

<https://dof.ca.gov/Forecasting/Demographics/>

### DRU Data Hub

<https://dru-data-portal-cacensus.hub.arcgis.com/>

### General Inquiry

[ficalpop@dof.ca.gov](mailto:ficalpop@dof.ca.gov)

## California Office of Data and Innovation

<https://innovation.ca.gov>

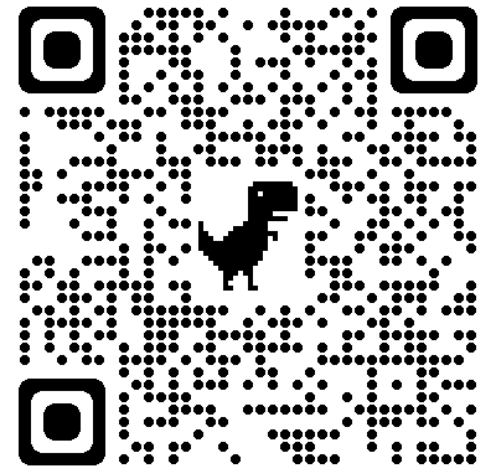
@californiaODI



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<https://cagov.github.io/data-infrastructure/data/footprints/>



# Thank you

Next GIS CoP Monthly Forum

Wednesday, March 27<sup>th</sup> , 2024

Questions or comments send to: [gio@state.ca.gov](mailto:gio@state.ca.gov)